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The Sharing Economy: a dive deep into the dynamic pricing strategy of AirBnB hosts

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1. Abstract

Purpose

The traditional hospitality industry has undergone significant changes since the advent of sharing economy platforms such as AirBnB, which have redefined the competitive landscape (Gibbs, Guttentag, Gretzel, Yao & Morton, 2018). Despite the differences between platforms and traditional accommodation providers, they share the use of the same profit maximization tool: the dynamic pricing strategy. This strategy is rather simple and requires data analysis skills, on one side hotels have trained professionals that implement it, on the other there are users with different cultural backgrounds, skills, and purposes (Gibbs et al., 2018). Understanding the dynamics of such strategy would help non-professional users to maximize their profits, and it would ultimately positively impact the platform itself because of the network effects.

Design

Three hypotheses were developed to analyze if the dynamic pricing strategy, the tenure (subscription time at the beginning of the study), and the average daily rate per location are correlated with hosts' average daily rate (performance). To understand the dynamics underlying the dynamic pricing strategy, it was made a distinction between three modalities of price change. The hypotheses were tested using data about AirBnB listings over a period of 21 months for over 1 million observations. The analysis was conducted using a Linear Fixed Effect and a Mixed Effect model applied to longitudinal data.

Findings

Using a dynamic pricing strategy can be effective also in the sharing economy platforms environment. Despite differences in the three modalities of price change, in the long run they result to be profitable, hence suggesting that hosts should adopt it according to their preferences. There is no evidence of a relationship between hosts' tenure and their ability to impact their ADR using the dynamic pricing strategy, it appears that the learning curve in such a complex environment is quite long.

Contrary to other findings (Wang & Nicolau, 2017), the average daily rate of the area influences the one charged by hosts, signaling that hosts can use it as a benchmark for their rates.

2. Introduction

2.1 Research rationale

One of the major players within the sharing economy is AirBnB which has been defined a disruptive innovator and has built its competitive advantage on an asset-light business model. The travel accommodation provider has launched its platform in 2008, since then it has served more than 30 million customers and in 2021 the company was valued at $113 billion, with a market share estimated to account for up to 20% of the vacation rental industry as whole (Akbar & Tracogna, 2018). The definition that AirBnB provides of itself is that of a *"a trusted community marketplace for people to list, discover, and book unique accommodations around the world*", this allows hosts to make profit from their underutilized assets, and guests to live an "authentic" travel experience with the benefits of a home (Zervas, Proserpio & Byers, 2017; Akbar & Tracogna, 2018). The entrance into the accommodation sector of the flexible capacity sharing economy platform is having a relevant impact on the fixed-capacity incumbents' performance. Statistics report that over 50% of AirBnB guests prefer its offering over a traditional hotel, this can be explained by several factors, but the price represent a major discriminant, and it appear that in Europe AirBnB is from 8% to 17% cheaper than hotels, whereas in the US it is between 6% and 17%.

Because of the implications that the data just mentioned can have, there is plenty of research on the topic and the different aspects of the phenomenon. Kumar, Jha, Damodaran, Bangwal & Dwivedi (2020), Liu & Yang (2018), Yi, Yuan & Yoo (2020) have focused on the factors that drive consumers' adoption of the sharing economy, Li & Srinivasan (2018) and Gibbs, Guttentag, Gretzel, Yao & Morton, 2018 have investigated the impact that AirBnB has had on the pricing strategy of hotels, Blal, Singal & Templin (2018) studied the impact of the disruptive platform on hotels' sales growth, and Lawani, Reed Mark & Zheng (2019) have investigated the relationship between reviews and price setting on online platforms, using AirBnB data to draw a sentiment analysis.

This research aims at filling two main gaps: the first one is related to the use and effectiveness of the dynamic pricing strategy applied by AirBnB hosts, the second one concerns the relationship between hosts' experience and their ability to implement an effective dynamic pricing strategy.

Multiple studies have investigated the effectiveness of the dynamic pricing strategy applied in businesses such as hotels and airlines, and they demonstrate that it is in fact effective, but these conclusions cannot be directly applied to AirBnB (Abrate, Sainaghi & Mauri, 2022). Several studies affirm in fact that AirBnB does not represent a threat for the hotel industry as it is a niche product, and its offerings are not a direct substitute to those of hotels, this means that it can't be assumed that

they respond in the same way when the same strategy is applied (Sainaghi & Baggio, 2020). Moreover, Gibbs et al. (2018) compared the use of dynamic pricing strategy between hotels and AirBnB hosts and they revealed that there is a difference between the two, however they did not measure the impact that such strategy has on AirBnB listings performance in terms of profit.
For what concerns the second gap to fill, hosts' experience is usually referred to as their degree of professionalization based on the number of listings they manage on the platform, and different studies have investigated the relationship between this and their performance (Sainaghi & Baggio, 2020; Abrate, Sainaghi & Mauri, 2022). This study instead will investigate the relationship between hosts' experience, measured by the length of their subscription in January 2016 (starting point of the analysis), and the application of a dynamic pricing strategy.
Considering the gaps in the literature, the purpose of this research is to enrich the existing body of literature by providing an additional perspective on the impact of the dynamic pricing strategy and of hosts' experience on their performance. Ultimately, this research could generate insights for AirBnB hosts on how to improve the performance of their listings.

The paper will be structured as follows: the next chapter will present a literature review of the main pillars of the topic analyzed, followed by the presentation of the conceptual model and the development of the hypothesis that will be tested in this paper. The third chapter will be focused on the analytical aspect of this thesis, introducing the dataset and explaining the variables included in the research. Right after the models employed in this study are presented along with an introduction of the type of data. Once an overview of the dataset is provided, it is presented a summary of the preliminary findings through descriptive statistics and the chapter ends with the examination of the main analytical results. In the fourth and last chapter conclusions are drawn based on the empirical results obtained through the analysis. The thesis ends leaving questions open for future research related to this topic.

2.2 Literature review

Before developing the hypothesis of this study and diving into the analysis, the main pillars of this research are summarized in the following paragraphs.

2.2.1 Digital platforms

We could think of digital platforms as the modern-age marketplaces, in which the presence of technology and of a much larger network to involve have transformed the way of doing business (Belleflamme & Peitz, 2021). Especially for small and medium-sized enterprises that struggle to remain competitive, digital platforms represents a great opportunity to improve their business strategy and remain competitive thanks to the improved matching, professional networks, and the more efficient assets utilization they provide (Cenamor, Parida & Wincent, 2019; Evans & Gawer, 2016). It is possible to distinguish different kinds of platforms according to the use that firms make of the underlying dynamics that they have common, these are transaction platforms, innovation platforms, integrated platforms and investing platforms. Transaction platforms act as intermediary between users facilitating the exchange or transactions between them; innovation platforms guarantee its users the access to a pool of external innovators to develop complementary technologies; integrated platforms share the characteristics of both innovation and transaction platforms; lastly, investment platforms allow users to act as a holding company by developing a platform portfolio strategy (Evans & Gawer, 2016). The figure below provides examples of each type of platform, distinguishing between private one (in grey) and public one (in pink), and the dimension of the bubbles indicates the market cap as for December 2015:

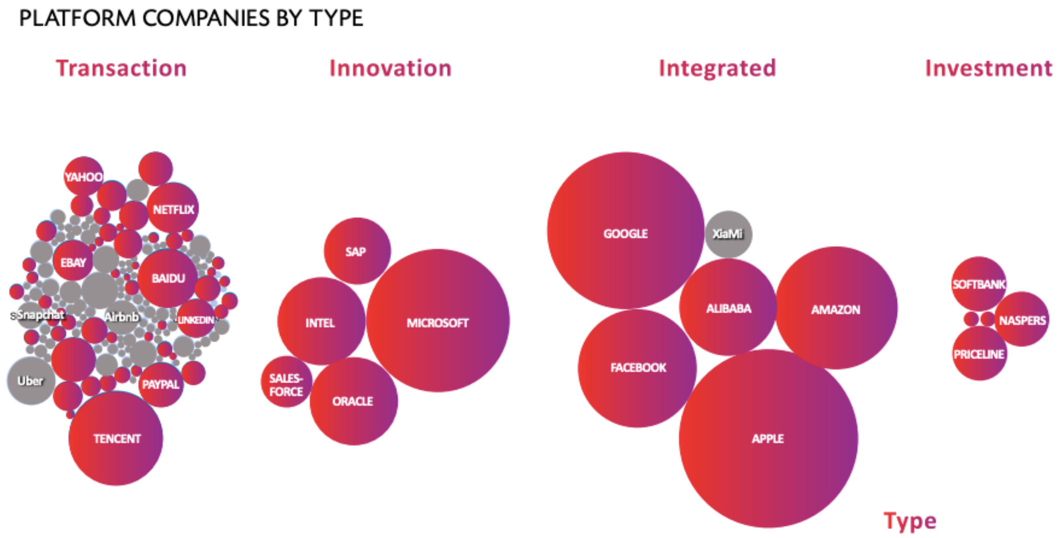

Figure 1 The rise of the platform enterprise (Evans & Gawer, 2016)

To remain competitive and respond to the challenges presented by the advent of platforms, incumbents adopted three main strategies: build their own platform, obtain platform capabilities through acquisition, and build platform through alliances. Independently of the strategy selected, incumbents must adapt their business model and hierarchical structure to function properly in this new ecosystem (Evans & Gawer, 2016).

Belleflamme & Peitz (2019) introduce the following definition of platforms: "*A platform is an entity that brings together economic agents and actively manages network effects between them*". This definition introduces a fundamental concept, the one of networks effects, these in fact are considered the key for the success of platforms (Evans & Gawer, 2016). Network effects describe the impact that an additional user has on the value of the product or service at hand, these can be direct or indirect, positive or negative and can originate within the group using the product or service (within group network effect) or between different group of users (Belleflamme & Peitz, 2019; Evans & Gawer, 2016). Direct network effects occur when the value of a product or service increases as more consumers adopt it, whereas indirect network effects depend on two or more group of users, that is, the member of one group join the platform, the more the others will benefit from it (Stobierski, 2020) Networks effects largely contribute to the evolution of a pricing strategy in which prices are cut to capture value by attracting more users. This is because companies that operate through platforms try to increase their market share by capturing as many consumers as possible by keeping prices very low at the initial stage to benefit from network effect (Hagiu, 2009; Stobierski 2020). Dou & Wu (2021) highlight the fact that there are companies *"embracing non pricing controls to incentivize user adoption".*

Platforms can be further distinguished between one-sided, two-sided, or multisided, depending on whom they derive value. In the case of one-sided platforms there is a single group of participants on which the platform can rely on to create value, multisided platforms extract value enabling the interaction between two or more group of users, while two-sided platforms facilitate the interaction between two groups of users (Almunawar, Ali & Lim, 2020). In this paper the focus will be on two-sided platforms that Hagiu (2009) defines as "bottlenecks between consumers and producers" because to create value both sides must participate in the same platforms. Moreover, two-sided platforms are subject to two types of competition that Li, Liu & Bandyopadhyay (2010) define as inside competition and outside competition; the former refers to the competition between platform users, the latter refers to the one that the platform itself experience with similar platforms to attract and retain users.

2.2.2 Sharing economy

Digital platforms facilitate the practice of sharing resources which has a long history but, combined with the large networks and the scalable technology they allow, today that traditional practice is defined as sharing economy (Mair & Reischauer, 2017). Sharing economy platforms have a great profit potential and have emerged as an alternative to fulfill multiple consumers' needs: AirBnB, Uber, BlaBlaCar and Lyft are just few examples of frequently used sharing economy platforms. The success of these platforms can be explained by the loosening of traditional organizational boundaries, such as those between producers and consumers, insourcing and outsourcing and products and services. The phenomenon has been extensively studied by researchers and there is consensus that the sharing economy can provide economic, environmental, and social improvements, moreover, the recent global economic recession has played a role in the increased reliance on the sharing economy (Majima, Fors, Inutsuka & Orito, 2021; Guttengag, Smith, Potwarka & Havitz, 2017). This innovative way of conducting business activities has spread over different markets, for example in the hospitality, car transportation services, parking sector, and even domestic animals market, and it represents an opportunity for consumers to become providers of products and services exploiting their underutilized resources. Sharing economy platforms are used by a multitude of geographically distributed individuals, feature that makes them an alternative channel to access goods or services traditionally provided by well-established firms, and that differ in terms of characteristics such as price, geographic location, and quality (Roma, Panniello & Lo Nigro, 2019).

The main strength of these platforms' users is their ability to offer very competitive prices with respect to incumbents, due to several reasons. First, resources made available are usually purchased by individuals for other scopes, which means that the related costs are almost entirely covered within those scopes, hence making the resource available with near-zero additional costs. Second, by leveraging platforms services any owner can provide goods or services, thus reducing barriers to entry, in turn attracting more and more users, included those with very low opportunity costs, pushing prices down even further (Roma et al., 2019). Researchers suggest that thank to the low cost of economic coordination, collaborative consumption enabled through these platforms can reduce hyper-consumption, pollution and poverty (Zhu, So & Hudson, 2016). Wirtz, So, Mody, Liu & Chun (2019) differentiate sharing economy platforms according to the business model they use, and their classification is depicted by the figure below:

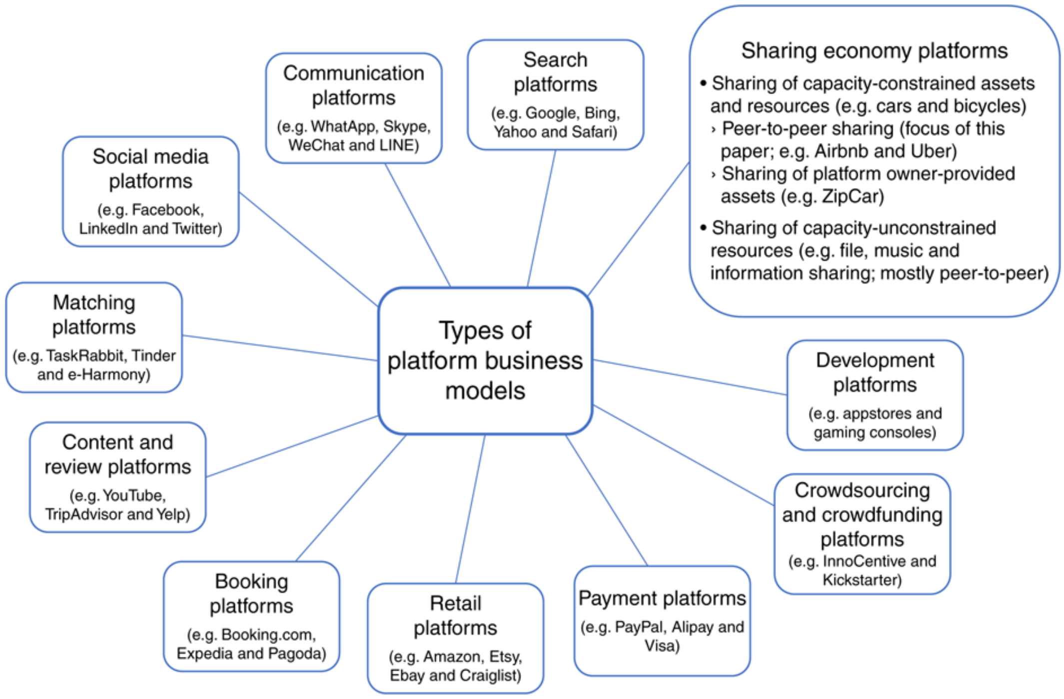

Figure 2 - Platforms in the peer-to-peer sharing economy (Wirtz et al., 2019)

Among the sharing economy platforms, the authors distinguish between those that share capacity-constrained assets and resources or capacity-unconstrained resources. The first category identifies those assets that cannot be used by multiple consumers at the same time, however digital platforms are particularly efficient in coordinating the utilization of such assets, while capacity-unconstrained assets are those that don't have this limitation (Wirtz et al., 2019).

Wirtz et al. (2019) make a further distinction of the sharing economy platforms according to two dimensions, asset provision and owners.

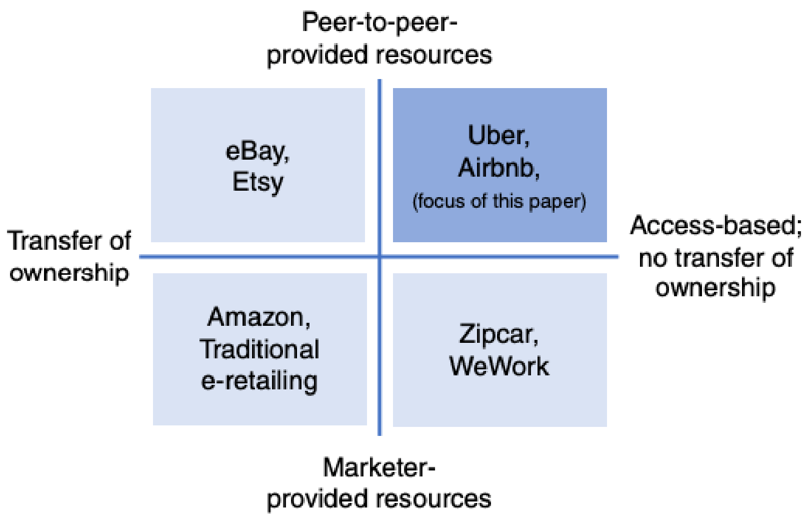

Figure 3- Platforms in the peer-to-peer sharing economy (Wirtz et al., 2019)

According to existing literature, the hospitality industry is the sector that was impacted the most by the advent of the sharing economy platforms, with AirBnB representing the major threat (Roma et al., 2019). Scholars have classified AirBnB as disruptive innovation and Blal, Singal, and Templin (2018) discussed it from the angle of business model innovation: the platform has invaded the market offering qualities and features different than those offered by incumbents, thus attracting a new customer base, and enlarging the existing one. When the platform was launched, hotels didn't see it as potential rival, in fact the company described itself as oriented to price conscious consumers who would not choose traditional hotels, however, as time has passed, AirBnB has become a substitute to hotels for more and more consumers as its features are becoming comparable, if not superior, to those of hotels, furthermore, AirBnB offers very often highly competitive rates as depicted by the comparison below.

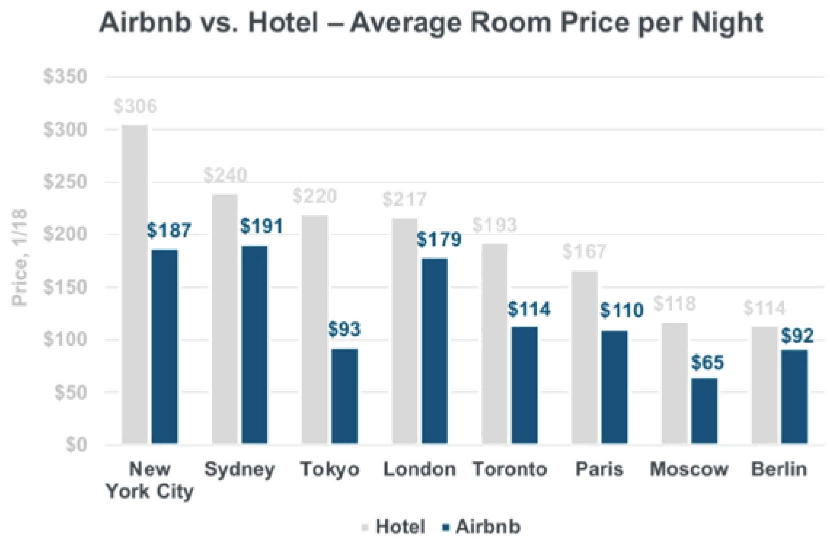

Figure 4- Airbnb vs. Hotels Price Comparison (Ping, 2020)

2.2.3 Dynamic pricing

A fundamental pillar for P2P accommodation platforms and, more generally, the hospitality industry is pricing. Consumers are highly influenced by the price in this kind of context because it is very often associated to the quality of the services they will receive (Wang & Nicolau, 2017; Masiero, Viglia & Garcia, 2020). Hotels and airline companies have been using a dynamic pricing strategy to maximize their profits. This strategy leverages on the fluctuations of demand to optimizes revenues, however it can't be applied in every industry as there should be some baseline characteristics to make it effective. The hospitality and the airline industry in fact are characterized by swings in demand justified by aspects such as seasonality and location, among others (Masiero et al., 2020; Nair, 2019). Hotels can employ this strategy to manipulate demand by leveraging on aspects such as the dimension of the structure both in terms of employees and of available rooms, location, seasonality, and the duration of the stay (Nair, 2019). The figure below illustrates the fluctuations of hotels' average prices in Rome, London and Paris over the last 13 months.

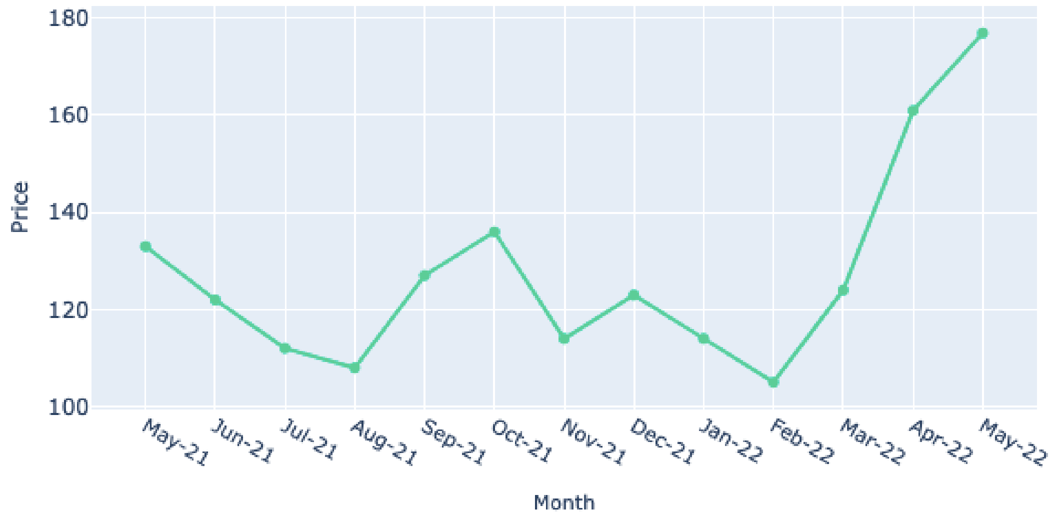

Figure 5 – Rome - Trivago Hotel Price Index 2022

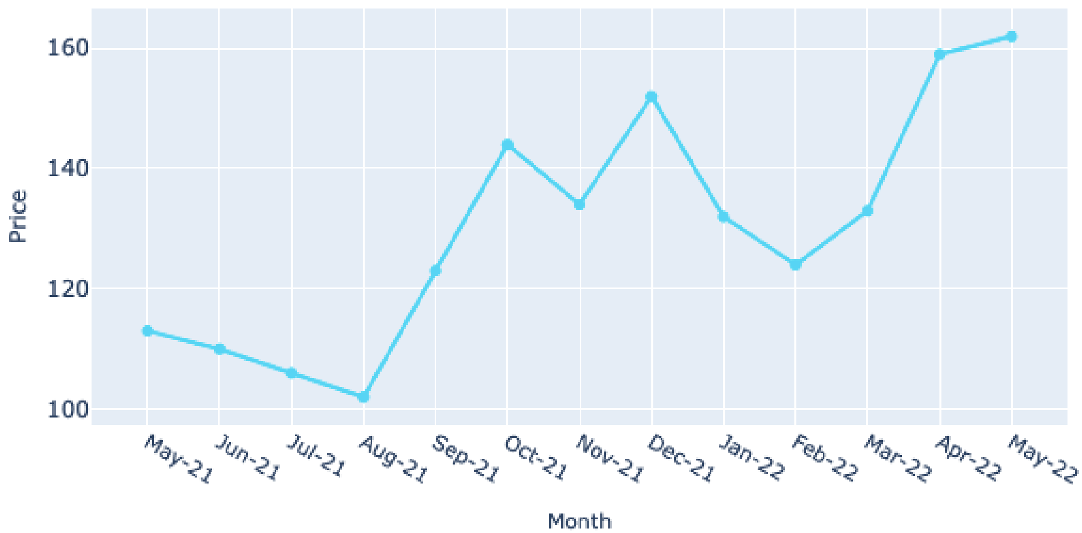

Figure 6 – Madrid - Trivago Hotel Price Index 2022

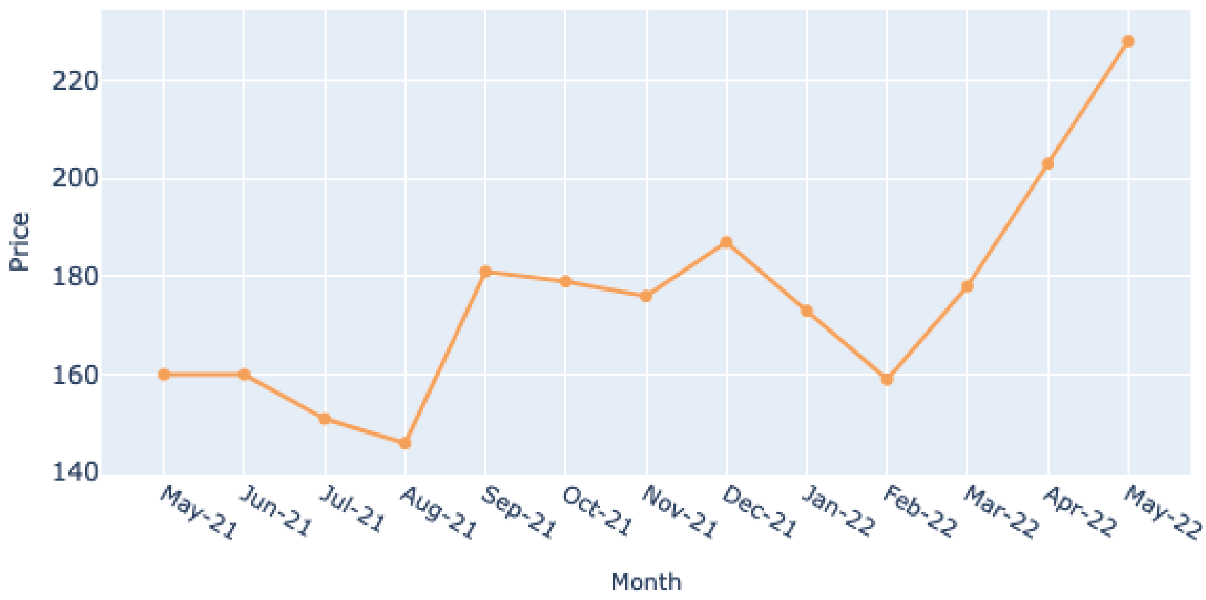

Figure 7 – Paris - Trivago Hotel Price Index 2022

Wang & Nicolau (2017) state that the price determinants for P2P accommodations are not the same as those of hotels, in fact, hotels primary determinants are those just mentioned, whereas on digital platforms it seems that the most relevant attributes are the hosts' characteristics such as super host status, number of listings and verified identities. Despite these differences, P2P platforms can still adopt the dynamic pricing strategy the environment is subject to the same external forces as the one of hotels (Wang & Nicolau, 2017).

This strategy requires data collection and analysis to make inferences and predictions on future demand and understand the optimal price level. For this activity, hotels can rely on trained professionals and sophisticated software that allow them to be precise. P2P platforms such as AirBnB instead, are used by different type of actors, there can be professionals as well as new market participants that want to make an extra profit from their underutilized resources and they may be lacking the technical knowledge required to develop such pricing strategy (Abrate, Sainaghi & Mauri, 2022). Hotels and AirBnB differ also in regards of the economic reasons behind their pricing decisions. Hotels use this strategy to maximize their revenues considering all the costs they must cover, whereas hosts may be motivated by different reasons. For example, hosts may desire to make an extra profit from their underutilized assets, or they may be willing to recover their fixed costs. However, the difference in the cost structure of the two business participants, AirBnB hosts can charge much lower prices thus increasing their competitiveness (Gibbs et al., 2018).

Because of the complexity of this pricing strategy and considering the importance that network effects, sharing economy platforms are helping their users to maximize revenues by developing specific algorithms that are able to suggest the optimal price taking into consideration various contextual factors. Uber for instance adopted an algorithm that computes prices considering both the distance and the duration of the ride, and it has a multiplier that increases the standard fee in times of high demand, hence maximizing drivers' revenues without damaging passengers' economic interests (Gibbs et al., 2018).

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2.3 Conceptual model

Consumers' motivation to use sharing economy platforms depends on several factors, some of them being sustainability, enjoyment, network effects, and, above all, economic benefits. It appears in fact that making monetary savings is the key driver to adopt innovative products and services and it directly influences consumers' positive attitude to participate in the sharing economy (Kim, 2019). AirBnB listings can be more competitive if compared to hotels, with rates estimated to be between 6% to 17% lower and this can be explained by the fact that AirBnB hosts have covered the main fixed costs such as rent or electricity, and have minimal labor costs. Due to the importance of pricing decisions, fundamental to manipulate demand, attract specific market segments and increase market-share, AirBnB has developed an algorithm that provides hosts a suggested price, based on listings' characteristics, however, contrary to what other platforms do (eg. Uber), hosts are still free to decide autonomously their weekly, daily or monthly rates (Gibbs, Guttengag, Gretzel, Yao & Morton, 2017). The accommodation sector is characterized by perishability, demand volatility and advanced bookings, factors that give it the perfect fit with a dynamic pricing strategy which consists in adjusting prices according to fluctuations in demand and other contextual factors (Gibbs et al., 2017; Abrate, Sainaghi & Mauri, 2022). Hotels widely use this strategic revenue management tool, as they have trained professionals that analyze past records, make predictions of demand fluctuations and set prices, but very often listings on AirBnB belong to non-professionals hosts that seek to make extra profits from their underutilized resources, and as demonstrated by Li, Moreno & Zhang (2015), they hardly ever use a dynamic pricing strategy. In fact, from their research it appears that non-professional hosts set their price when they list their accommodation and don't respond to fluctuations in demand, making an average daily revenue and an occupancy rate of 16,9% and 15,5% respectively lower than professional hosts (Li et al., 2015). The consequence of these results is that hosts that don't see the revenues they expected, may prefer to leave the market, and this in turns negatively impacts the platform. In fact, as a two-sided market, it is influenced by network externalities, meaning that as the user-base decreases the value users can derive also decreases (Li et al., 2015; Goldenberg, Libai & Muller, 2010).

As mentioned earlier, hotels use a dynamic pricing strategy and this has been widely analyzed and confirmed by previous research, as stated by Abrate et al., (2022), however they found out that there is a literature gap concerning the impact that such strategy has on AirBnB listings, they say in fact that only three studies focus solely on that, and in light of this the following hypothesis will be tested:

H1a: Hosts adopting a dynamic pricing strategy have a better performance than those that don't.

When selecting their pricing strategy, hosts can decide whether to increase prices or to live them as they are. Such decision is a key determinant of their success, it appears in fact that consumers tend to make a direct correlation between the price they pay and the quality they expect to receive, and price is the main variable that affects consumers' experience (Magno, Cassia & Ugolini, 2017; Pappas, 2019). Considering this, hosts should carefully decide the range of price change to avoid incurring two major risks: pricing their accommodations too high could make them lose potential medium spending guests, whereas pricing them too low could make their listings be perceived as low-quality ones. Lee & Deale (2021) found out that when prices are too low compared to similar listings in the same location, consumers' risk perception increases as well as a lack of trust. Pappas (2019) in his study highlights the fact that prices highly influence purchasing decisions of consumers, and he reiterates the fact that consumers use it to evaluate product superiority or excellence.
These findings are based on consumers' perception of prices considered at only one point in time, but it could be reasonable to assume that when prices are decreased too often, the perception of the accommodation could be negatively impacted, on the other hand, price increases could make consumers believe that the house is in fact valuable, in turn impacting the ADR of hosts.
With this study I want to investigate both the impact that the dynamic pricing strategy has on hosts' profits and the difference in impact given by the frequency of the modalities of price changes, hence the following hypothesis is formulated:

H1b: It can be identified a difference in impact in the modalities of price change.

As aforementioned, hotels rely on trained professionals to manage their pricing strategy, which is a time consuming and data-driven activity that allows to forecast demand and seasonality (Abrate, Sainaghi & Mauri, 2022). Koh, Belarmino & Kim (2019) demonstrated that there is a positive correlation between the degree of experience of professionals and the application of the dynamic pricing strategy, it seems in fact that professional hosts have higher revenues than non-professional ones. Other research instead demonstrated that hosts that don't achieve the expected results tend to leave the market (Li et al., 2015). However, these studies considered the degree of professionalization as the number of listings of each host and not as the duration of their subscription period. The interplay of the sharing economy and digital platform is a relatively new market environment, in which traditional market dynamics may not apply, and it could be the case that also trained professionals need to learn how to behave on them (Magno et al., 2017). Assuming that the number of listings can be a reliable proxy for the degree of professionalization (or experience) of hosts, does not consider the evolution of hosts and their behavior over time. Moreover, hosts success is not only related to the pricing strategy, but also to factors such as marketing or welcoming activities that generate network effects (Magno et al., 2017). Pappas (2019) states that social interactions between hosts and guests are a fundamental aspect that impacts the perception of the consumer experience, and this highlights the fact that hosts communication skills are another key determinant of their success.

In this paper I am interested in observing the relationship between hosts tenure and their performance to evaluate a potential learning curve, however in this study hosts' tenure is intended as the length of their subscription period when the study begins to keep the information of their potential improvement over time. For this purpose, the following hypothesis will be tested:

H2: Tenure is a confounder for the association between hosts' performance and dynamic pricing strategy.

Among the essential attributes for hotels, their proximity to popular areas, beaches and monuments is considered the one that can have a greater impact on room prices and consumers' choices, directly impacting the profitability of the structure (Balaguer & Pernìas, 2013). Napierala & Lesniewska (2014) considered the following location-based factors as key determinants of accommodation prices: location in the city center or in the tourism business district, distance from the city center, distance from other competitors or the main transportation nodes. According to their research, those factors highly impact hotel prices, however, as previously observed by Abrate et al. (2022), it is not always the case that hotels' dynamics apply also in the sharing economy context. Wang & Nicolau (2017) observed in fact that location directly influences hotels' prices, but the same is not true for AirBnB accommodation prices that instead are more impacted by hosts' characteristics. On the other hand, Gyodi & Nawaro (2021) have examined how AirBnB prices are related to location-based attributes and have found a positive correlation between these two variables. Listings located in the same area share latent characteristics other than their proximity to specific attractions, these could be neighbors acceptance of tourism activities and the continuous flow of people in their building, or if the area is safe at night (Pappas, 2019). To see if location impacts hosts' profitability also in the context of sharing economy, and specifically on AirBnB listings, I want to observe how much the ADR of each host is related to the one of other accommodations with the same zip code, The correlation between the ADR of individual hosts and the one of the area aims at keeping the information about those latent characteristics that might impact price. For this purpose, hypothesis 3 is developed:

H3: Hosts' profits are correlated to average daily rate of their zip-code.

3. Analysis

3.1 Research design

In the next paragraphs it will be examined and explained the data set used for this study and the methods of analysis.

Data used to test the hypothesis were collected from previous research. Such data were drawn by AirDNA, considered one of the most comprehensive sources of AirBnB listings. The data set in fact included information about Airbnb listings in the state of California (US) for 20 months, from January 2016 to September 2017.

3.1.1 Dataset and variables

AirBnB is among the most used accommodation platforms, hence, the dataset created through the analysis can be considered a reliable source of information. The initial dataset included over 7 million observations and 33 variables, and it has gradually been reduced to keep only the variables and observations relevant for the purpose of this study. The figure below demonstrates the process followed for the dataset reduction.

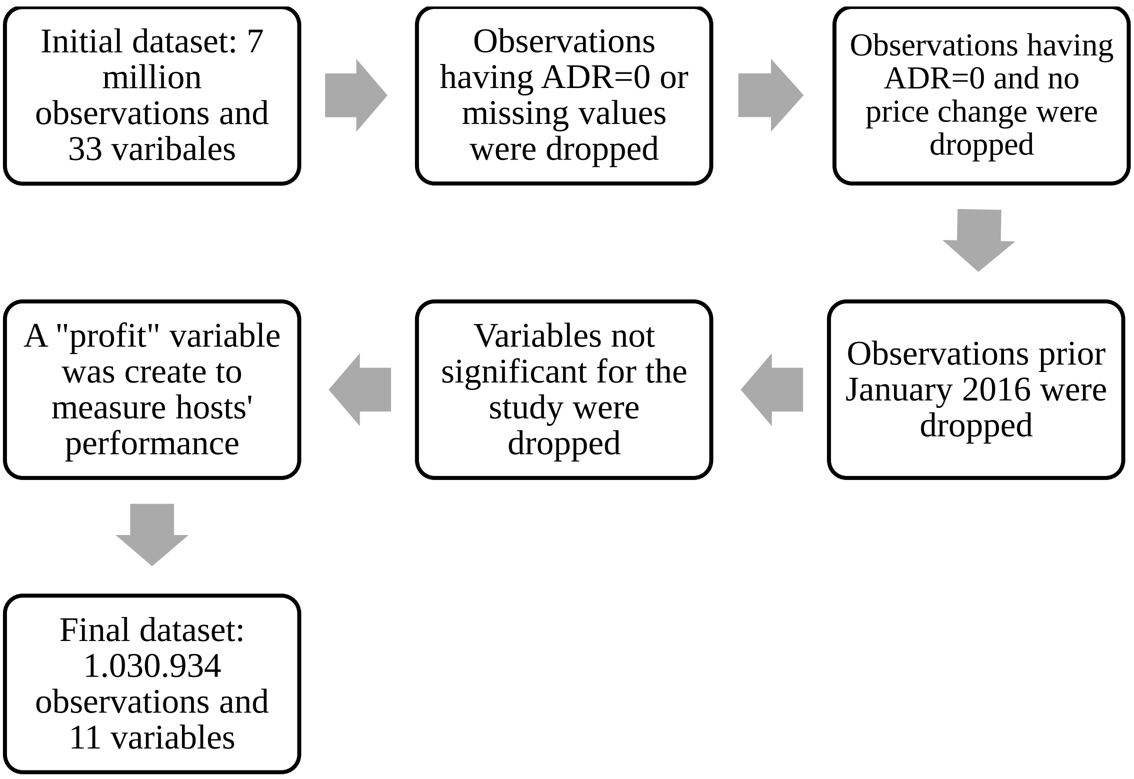

Figure 8- Flowchart

From the reduced dataset, containing slightly over one million observations, it is possible to analyze hosts' behavior to further examine the dynamics of price change, whether hosts' tenure has an impact on the choice of the strategy and a comparison with the overall performance of the neighborhood.
To better explain the reasoning behind the choice of the final variables included in the dataset and the conceptual framework discussed earlier, a DAG has been drawn.
A causal DAG (Directed Acyclic Graph) is a visual representation that displays an investigator's a priori assumptions about the relationship between variables also defined as the exposure (independent variable), outcome (dependent variable) and covariates (other variables in the study, they can be of different type). The peculiarity of this type of graph is that it is acyclic, meaning that there are no directed cycles (Glaymour, 2006).

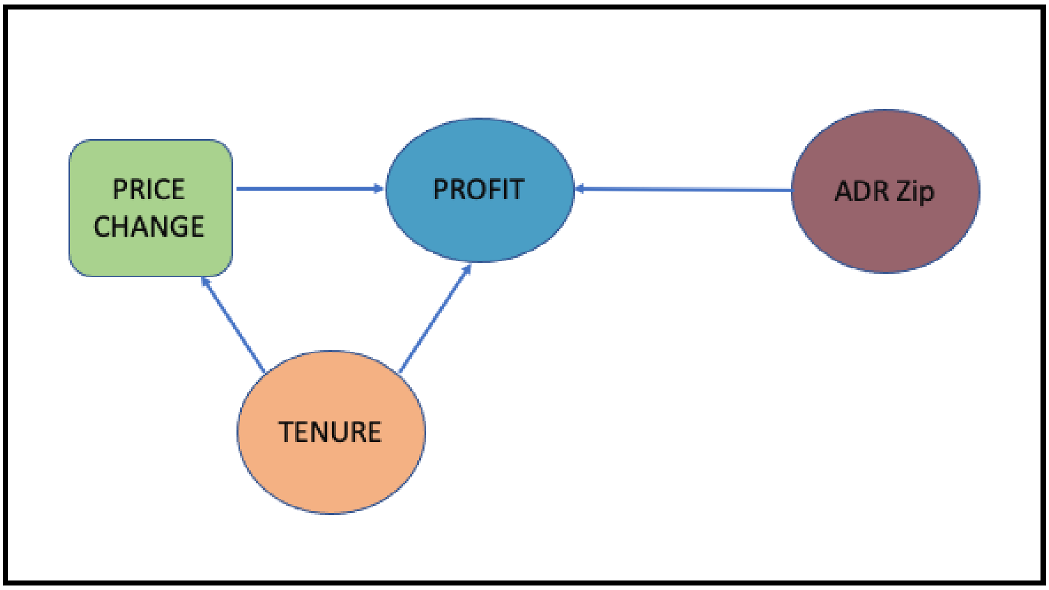

Figure 9 - Causal DAG

In this analysis the exposure is the tendency to change prices over time, the outcome is the hosts' performance, and the covariates are the tenure and ADR zip. The underlying assumptions are the following: changing the price clearly has an impact on the overall profit, as stated by previous research (Gibbs et al., 2017; Li et al., 2015; Abrate et al., 2022), however also hosts' tenure plays a role in the outcome. This latter variable is the confounder, that is a variable that has an impact both on the exposure and on the outcome (Elwert, 1970. An experienced host may have understood the dynamics of the market and hence she may be able to set the right price at the right time, but she may also have learned that factors such as kindness, availability, and communication, among other, can impact her performance. ADR zip, which identifies the average revenue of the neighborhood, has been included because hosts could consider it as a benchmark to set their price, and in this model, it is the predictor. A predictor is a variable that has direct impact on the outcome, and it has no correlation with the exposure (Elwert, 1970). It can be helpful in the analysis to determine how a specific host or group of hosts is performing compared to their average neighborhood profit, it is assumed that this variable will only have an impact on profit, not on the tendency to change price.

The table below summarizes the variables and measures used to conduct the analysis; details will be provided right after.

Variables	Description	Measure
ADR	Dependent variable	Proxy of hosts' monthly performance
Price change	Independent variable: Exposure	Propensity to change the price over observed time
ADR per zip-code	Independent variable: Predictor	Proxy of monthly performance per address zone
Tenure	Independent variable: Confounder	Hosts' experience as for January 2016

Table 1- Variables

ADR, acronyms of average daily rate, is the dependent variable in the study and it is the proxy used to measure hosts' monthly performance in terms of profit, it is a function of price per night, number of rented rooms over available rooms and number of nights per rented room, and it was already available when the initial dataset was downloaded.

$$ADR = \frac{price_A * \frac{n\ rented\ rooms_A}{n\ available\ rooms_A} * \ n\ of\ nights_A + \cdots + price_Z * \frac{n\ rented\ rooms_A}{n\ available\ rooms_Z} * \ n\ of\ nights_Z}{\frac{n\ rented\ rooms_A}{n\ available\ rooms_A} * \ n\ of\ nights_A + \cdots + \frac{n\ rented\ rooms_A}{n\ rented\ rooms_Z} * \ n\ of\ nights_Z}$$

Equation 1 - ADR

Since this variable takes into consideration the number of rooms rented per month, the price of each room, and the duration of stay per room, it can be used for the comparison of the monthly performance of single hosts and between multiple hosts. Moreover, it also allows for standardized comparisons between different types of listings because it functions as a weighted average.

The first independent variable, or outcome, considered in the study is *price change*, and it measures the propensity of each host to change price, or, in other words, adopting a dynamic pricing strategy over time. In the initial dataset, this variable was classified into three different sub-variables, total number of price changes, number of price increases and number of price decreases. However, to measure the tendency to take on a dynamic pricing strategy, the three modalities just mentioned, were used to create a categorical variable with four modalities:

0. No price change: the host has never changed the price over time.
1. Increases > Decreases: the host has performed more price increases than decreases.
2. Increases < Decreases: the host has performed less price increases than decreases.
3. Increases = Decreases: the host has performed the same number of price increases and decreases.

This variable has been created with the intention to measure the difference in impact of price increases and/or decreases. It was chosen as such a variable instead of a dummy one (1= price change, 0= no price change) because the focus of this analysis is not just verifying the impact of the propensity of price change on the outcome, but also the difference in impact given by increases or decreases. Hence, it was decided to keep track of information about price changes by categorizing the tendencies of the hosts to increase or decrease the price, along with their propensity to price change.

The predictor, ADR per zip code, is the independent variable that indicates the average revenue of the neighborhood, and it has been included to observe if and, eventually, how much, it influences hosts' profit. This variable was not modified, it was part of the initial dataset.

The confounder in this model, tenure, is used as a proxy for the level of experience that hosts have. In this analysis I am not interested in observing how this variable changes overtime, instead, I want to investigate the impact it has on host strategy adoption (dynamic pricing or not). For this reason, it has been taken into account only the initial level of tenure of each host, hence, the level in January 2016.

3.2 Methods

After a careful observation of the longitudinal data available for this study, the hypotheses have been tested using two different models: the linear fixed effects model and the linear mixed effects model. The choice of using two different models is because it is not always easy and intuitive understating the dependence or independence of certain variables, and a wrong model can lead to distorted results. Specifically, distorted results are caused by the case of pseudo-replication, that is, the failure to recognize a lack of statistical independence in the dataset (Clark & Linzer, 2014).

3.2.1 Longitudinal data study

Longitudinal data are commonly used in medical research but are helpful for different kind of research activities. The peculiarity of this type of study is that the repeated measurements are conducted on each individual over short or long periods of time to observe fluctuations in behavior, emotions or health status. Longitudinal data and cross-sectional data (when individuals are measured at one period of time) are both valid and widely used but longitudinal data have some advantages: they allow to measure within-sample change over time, the duration of events and the timing of various events. In fact, participants' exposure status is recorded at multiple follow-up times and under different experimental conditions, giving research the possibility to observe individual patterns of change (Laird & Ware, 1982; Diggle, Heagerty, Liang & Zeger, 2002).

Moreover, a longitudinal study avoids the cohort effect, that is, the effect that sharing specific characteristics such as age or experiences can have on the outcome, in fact, when differences in individuals are observed, it is less likely that these are imputable to cultural, socio-economical, or generational differences (Carlson, Sroufe & Egeland, 2004).

Longitudinal analysis is a type of linear regression in which the observations are not independent because the same individual has multiple observations, and this has two main implications: random effects and serial correlation. Random effects reflect the heterogeneity among individuals because of factors difficult to measure, and the serial correlation reflects the possibility that repeated measurements from the same individual over time can be correlated (Das, 2014; Diggle, Heagerty, Liang & Zeger, 2002).

The longitudinal data analysis has been performed using the mixed-effect model and the fixed-effect model, and details on the two models will be provided in the next paragraphs.

3.2.2 Linear mixed-effects and fixed-effects models

Statistical models in general aim at understanding how the dependent variable (hosts' ADR) is some function of the independent variables (price change, ADR per zip-code and tenure). The way in which models are defined depends on what is believed about the values of the independent variables.
When the values of the independent variables are estimated to be fixed, the main assumption is that they represent the entire population of interest and there are no other relevant factors to examine, and the model to use is the fixed-effect model.
When instead the values of an independent variable are believed to be drawn at random from a larger population, it is more appropriate to use a mixed-effects model.
The linear mixed-effect model and the fixed-effects one, can be considered a variation of the general linear model. The GLM allows for the estimation of the relationship between two or more variables and different effects, and it can be applied to a variety of data. However, this model assumes a very basic data structure and does not allow the modeling of a wide range of relationships and dependencies between units of measurement. The GLM can be represented as follows:

$$Y_i = a + bx_i + e_i$$
$$corr(e_i, e_j) = 0$$

where a is the estimated value of the population and it is a fixed parameter, x_i is the independent variable, b is the regression coefficient, and it represents the impact of the independent variable on the outcome, whereas e_i represents the causal variations that are independent from one another.
In the fixed effects model, the individual specific effect is correlated with the independent variables and the time invariant factors are excluded from the model by taking the difference between each observation with the within-group mean values in order to get rid of the individual specific effect.
Graphically, a fixed effect model assigns the same slope to the whole population, considering however a different baseline per individuals.
The fixed effect model assumes the uniqueness of effects and the independence of the measurements. These fundamental assumptions may not hold in the case of related measurements, data with hierarchical structures or data with multi-level measurements. In these cases, the linear mixed effect model can be applied.
However, the assumptions of uniqueness of effects (fixed effects) and independence of the measurements (independent errors) are not fulfilled in certain cases, such as when there are related measurements, data with hierarchical structures or data with multi-level measurements. In these cases, the linear mixed-effects model can be applied: in this model there is not a unique fixed value to be

estimated and the casual variation are not independent form one another. The arithmetic notation of the LMM is the following:

$$Equation\ 1.\ y_{ij} = a_j + bx_{ij} + e_{ij}$$

$$Equation\ 1.1\ y_{ij} = (\bar{a} + a'_j) + bx_{ij} + e_{ij}$$

$$Equation\ 2.\ y_{ij} = a_j + b_j x_{ij} + e_{ij}$$

$$Equation\ 2.1\ y_{ij} = (\bar{a} + a'_j) + (\bar{b} + b'_j)\, x_{ij} + e_{ij}$$

$$Equation\ 2.2\ y_{ij} = \bar{a} + a'_j + \bar{b}\, x_{ij} + b'_j\, x_{ij} + e_{ij}$$

where y_{ij} and x_{ij} are the observed variables for subject *i* in the cluster *j*, $\bar{a}$ and $\bar{b}$ are the fixed effects, a'_j and b'_j are the random effects computed in cluster *j* and expressed as a deviation from their mean and e_{ij} is the error associated to each subject *i* in the cluster *j*. A cluster can be defined as individuals in the same group that share some characteristics that are not considered in the model (Diggle et al., 2002).

The mixed model allows the extension of the general linear model to data analysis problems where the data structure does not fit naturally, as in the case at hand, in fact using a GLM would have led to distorted results because I would have considered each individual as equivalent, in fact Equation 1 assumes a different baseline level for each host but assigns the whole population the same slope.

The LMM instead allows to consider random effects, for which the basic premise, as stated by Diggle et al. (2002), is that "*there is natural homogeneity among subjects in a subset of the regression coefficients, for example the intercepts*". When the homogeneity of individuals is not limited to the baseline level as in the case at hand, it is captured by the introduction of the random slope together with the random intercept (Equation 2). In the mixed effects model, the individual specific effects are uncorrelated with the independent variables and the coefficients of all variables in the model are estimated, and there is no fixed individual specific effects. Graphically, in the mixed effects model, individual differences are captured by the random slope and the random intercept. Equation 1.1 and 2.2 further highlight the difference with the GLM, clearly showing the presence of fixed and random coefficients.

3.2.4 Descriptive statistics

To fully understand the dataset, several graphs were created, using the basics of descriptive statistics. Through these, it was possible to understand and observe the trends underlying the available dataset. The following paragraphs summarize the main preliminary findings.

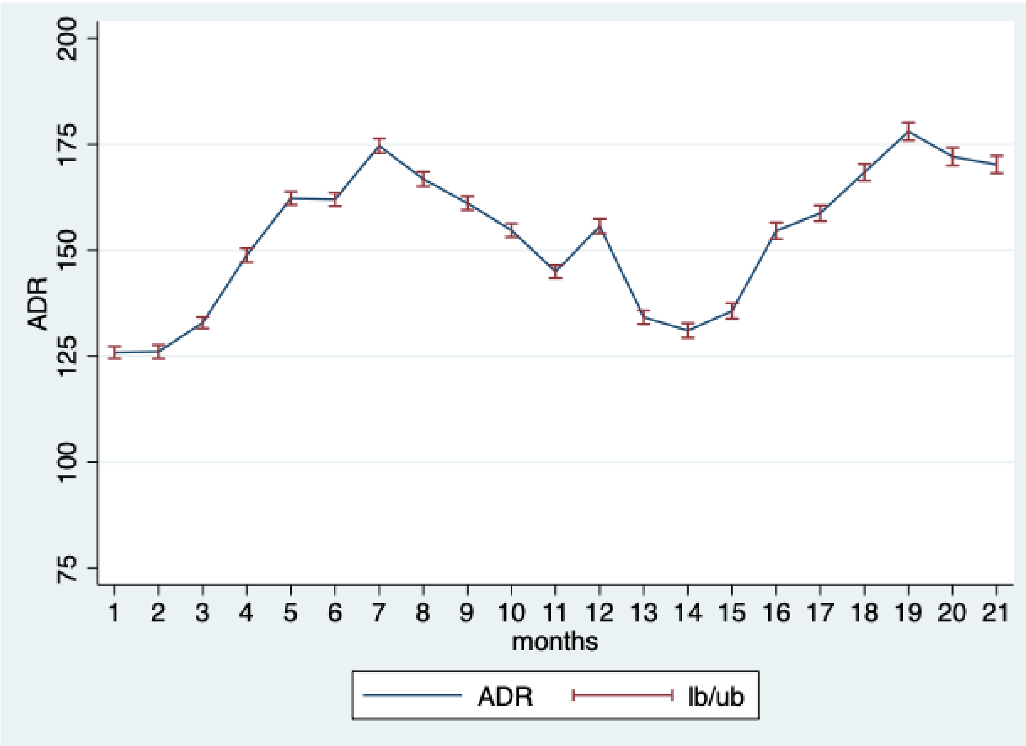

Figure 10 - Broken-line - summary

The purpose of the above broken-line graph is illustrating the tendency that the data are following. On the x-axis are represented the points of time considered in the research, on the y-axis there is the overall profit for that time, and the red lines represent the confidence intervals for every point in time. In this representation the four modalities of price change (0, 1, 2 and 3 as mentioned in section 3.1.1) are grouped together, and this is because in this case the focus is on the overall pattern followed by the average daily rate, non-related with the impact of the dynamic pricing strategy. It can be observed that there are positive peaks in July and negative ones in February, in this case the assumption that can explain these is that they depend only on seasonality and not on the prices selected in that point in time. In fact, data were collected from AirBnB listings in the State of California, specifically from the County of San Diego, which is known to have a particularly favorable weather during summer, that’s when tourism flows could reasonably increase.

Figure 11- Broken-line – Details

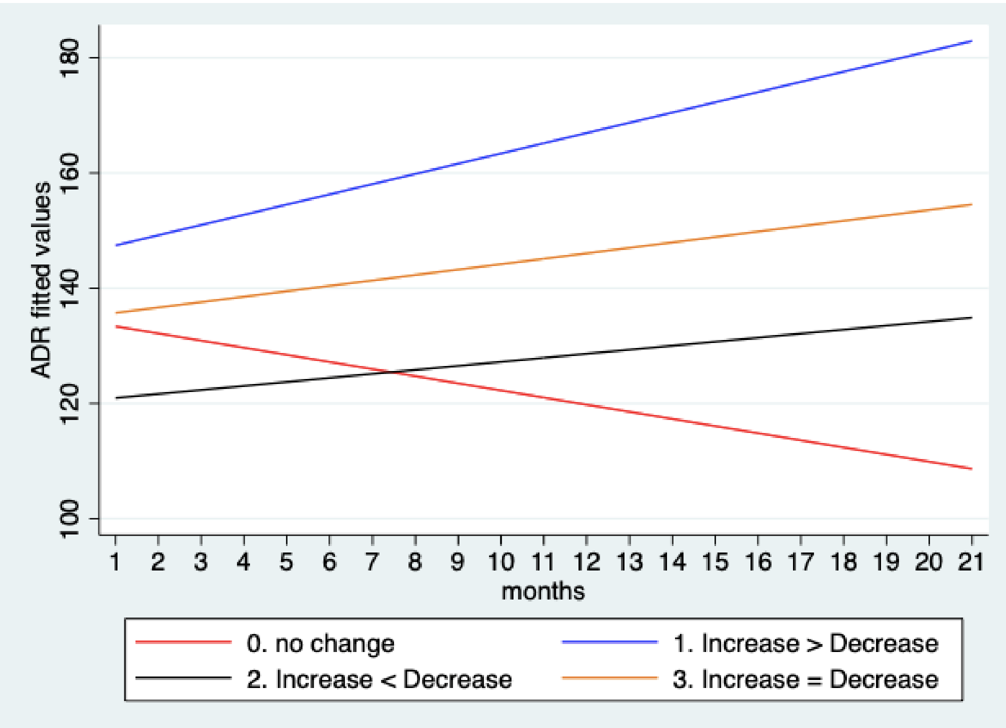

Figure 12- LFIT – Predicted values

Figure 2 is an "in-depth analysis" of the first one, in which the trend observed earlier is divided between the four modalities of price change. It can be observed that among the 4 modalities, performing more price increases than decreases leads to a better and more constant profit. We observe that there are seasonal fluctuations, but the impact is different between the four modalities. In fact, when hosts perform no changes, more decreases than increases or the same number of increases and decreases, they experience wider fluctuations in profit, whereas in the case of Increases>Decreases, the range of fluctuation is less variable and overall profits are higher. Moreover, it can be detected an overall positive trend in all the modalities except for n.2 (Increases < Decreases), where successive peaks (both positive and negative) are worse than the previous ones. Modality n.2 and n.3 (Increases = Decreases) follow a similar trend.

The tendencies just described are further confirmed by Figure 3, which helps making a very basic arithmetic prediction about data using straight lines. The purpose of this graph is analyzing the trend without covariates, just considering the profit in the four modalities of price change without taking track of the impact of tenure and ADR per zip-code, moreover, this kind of graph does not consider the panel nature of the data. The result is that performing more price increases than decreases is the better strategy, and performing no price change, hence non-adopting a dynamic pricing strategy is the worse option. This graph further confirms the underlying positive trend previously mentioned.

Figure 13- Scatterplot – ADR distribution

To conduct an exploratory analysis to observe potential differences in the four modalities of price change and understand how profits are distributed between them, it was chosen a scatterplot. This kind of graph can detect different kinds of correlations between variables. On the x-axis are represented the 21 months considered in the analysis and on the y-axis are reported the overall profits. In this case profit is not intended as ADR (average daily rate), instead it is the average of each individual in the considered month, and this is represented by the dots in the graph. This graph confirms what has been previously observed: performing more price increases than decreases leads to a better overall performance and less fluctuations.

Because of the non-linearity of the data applied in the model, it was introduced a cubic spline which is a third-degree polynomial that allows for smaller margins of error. In the spline each function is tied to the successive one by “nodes”. In the model at hand three nodes where identifies: the first one is in July 2016, the second one in February 2017 and the last one in July 2017. The decision to include these nodes is justified by what observed in the descriptive analysis, there are in fact three peaks in correspondence of the selected nodes.

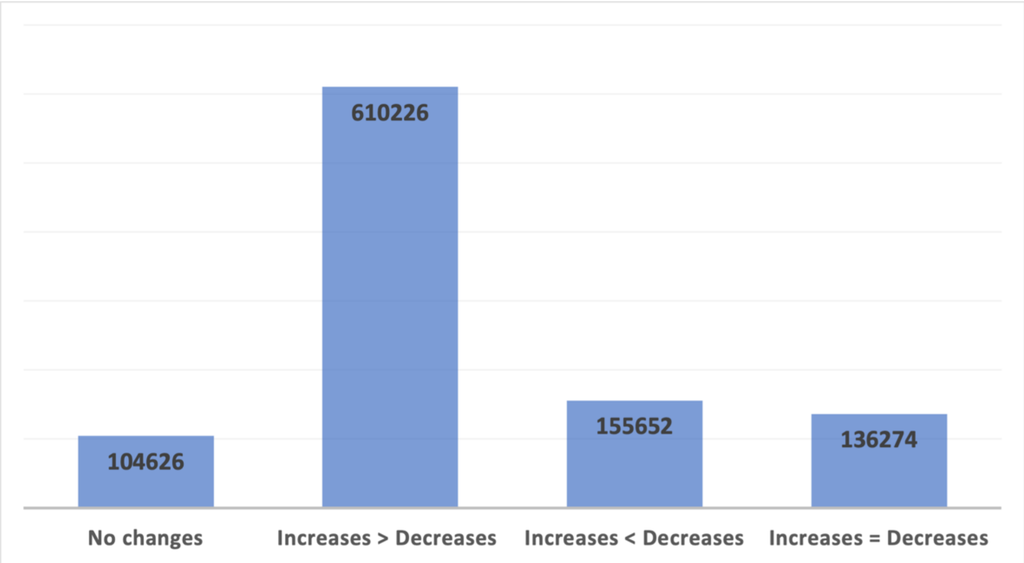

Figure 14 - Frequency table

The histogram above represents a frequency of the modalities of price change in the observed population. In percentage terms it appears that 10% of the population does not make price changes, 60% makes more price increases than decreases, 15% makes more price decreases than increases and 13% makes the same number of changes. What emerges from these figures is that 40% of the observed population could have performed better by selecting a different strategy, and if these numbers can be generalized to the rest of the population, it means that this research could help hosts improve their performance, and in turn, help platforms such as AirBnB increase their engagement because of users' better profits.

3.3 Results

3.3.1 …From the fixed-effects model

ADR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
time	.4175169	.0215805	19.35	0.000	.3752198	.4598139
change						
1. increase>decrease	0	(omitted)				
2. increase<decrease	0	(omitted)				
3. increase=decrease	0	(omitted)				
adr_zipM	0	(omitted)				
exp	0	(omitted)				
_cons	40.48734	.3962727	102.17	0.000	39.71066	41.26403

Table 2 The Fixed effects model

This model analyzes the effect of time, the other variables are excluded from the analysis as they are time variant factors. In Table 2 it can be observed that the coefficient of time is positive and statistically significant (coeff. 0.4175169; p-value 0.000; C.I.: 0.3752198 – 0.4598139), this means that with respect to the baseline level of 40.5$, the ADR of hosts increases of an amount equal to 0.42$.

To observe how the modalities of price change interact with time, the above model should be deepened, and the following tables provide an overview of the analysis.

ADR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
time	.117939	.0898213	1.31	0.189	-.05811	.293988
change						
0. No change	0	(omitted)				
adr_zipM	0	(omitted)				
exp	0	(omitted)				
_cons	36.9883	1.248787	29.62	0.000	34.54069	39.43592

Table 3 The FEM: no change

Table 3 shows the details of the effect of time when no price change is performed by hosts. It appears that compared with the overall scenario illustrated in Table 2, the baseline coefficient is lower as well as the increase over time. However, the p-value in this case is 0.189 (C.I. -0.05811 – 0.293988), meaning that the observed results in this case are not statistically significant, it could be the effect of time is likely due to chance.

ADR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
time	.6217458	.0270996	22.94	0.000	.5686314	.6748603
change						
1. increase>decrease	0	(omitted)				
adr_zipM	0	(omitted)				
exp	0	(omitted)				
_cons	42.03096	.5171449	81.28	0.000	41.01738	43.04455

Table 4 The FEM: Incraese>Decrease

The scenario illustrated by Table 4 is related to modality 1, when the host performs more increases than decreases. It can be observed that not the baseline level in this case is higher compared with the previous results (_cons 42.03096), but also the increase over time is so, in fact time has a coefficient of 0.6217458 and a positive p-value (0.000). This result highlights that performing more price increases than decreases has a positive impact on the ADR, and such impact is in fact relevant.

ADR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
time	.1493492	.05196	2.87	0.004	.0475086	.2511898
change						
2. increase<decrease	0	(omitted)				
adr_zipM	0	(omitted)				
exp	0	(omitted)				
_cons	42.1057	.9511263	44.27	0.000	40.24151	43.96989

Table 5 The FEM: Increases<Decrease

When hosts perform more price decreases than increases, the baseline level is 42.1057, lower than the opposite modality and time has a positive coefficient which is also statistically significant (p-value 0.004; C.I. 0.0475086 – 0.2511898).

ADR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
time	-.0705542	.0568412	-1.24	0.215	-.181962	.0408535
change						
3. increase=decrease	0	(omitted)				
adr_zipM	0	(omitted)				
exp	0	(omitted)				
_cons	36.33498	1.053922	34.48	0.000	34.26931	38.40065

Table 6 The FEM: Increase = Decrease

This is the last modality of price change considered in this study. Observing the constant term, it appears that this is the worst modality, it has in fact the lowest coefficient if compared with the others (36.33498), moreover, at every successive point in time, the ADR decreases, as depicted by the negative coefficient of time (-0-0705542). However, this evidence is not statistically significant considering the p-value of 0.215.

According to the above results, Modality 1 is the most profitable one, followed by it opposite.

The results of this first model, which considers only the effect of time, demonstrate that apart from the modality of no price change and same number of increases and decreases, which turn out not to be statistically significant, it can be inferred that time is a statistically significant factor. This results further demonstrates that using a mixed effects model can lead to a clearer and more detailed interpretation of the interrelationship of the considered variables.

3.3.2 …From the mixed-effects model

ADR.	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
timesp1	.0917319	.114567	0.80	0.423	-.1328153	.3162791
timesp2	-1.186397	.1501055	-7.90	0.000	-1.480599	-.8921957
timesp3	1.579639	1.11104	1.42	0.155	-.5979587	3.757237
Change						
1. increase>decrease	-10.47503	1.448446	-7.23	0.000	-13.31393	-7.636125
2. increase<decrease	-22.67355	1.816517	-12.48	0.000	-26.23386	-19.11324
3. increase=decrease	-15.75118	1.981748	-7.95	0.000	-19.63533	-11.86702
time	0	(omitted)				
cambio#c.time						
1. increase>decrease	1.066003	.1184868	9.00	0.000	.833773	1.298233
2. increase<decrease	.5421128	.1373844	3.95	0.000	.2728444	.8113811
3. increase=decrease	.4223962	.1406956	3.00	0.003	.1466378	.6981545
adr_zipM	.9725248	.0028266	344.07	0.000	.9669849	.9780647
exp	-.4698582	.3296531	-1.43	0.154	-1.115966	.1762501
_cons	46.05967	1.353695	34.03	0.000	43.40648	48.71286

Table 7 - The LMM

The table above summarizes the results of the analysis conducted on the data.

The impact of price change is considered both with and without time progression to evaluate it in the short and long run. It can be observed that the time progression has not been examined singularly, this is because its impact is included in the spline.

Focusing on the effects of the modalities of price change it can be observed that they have a significant p-value if compared with the modality of no price change (0.000 for the three modalities of change). This means that changing the price has an impact on the final ADR of the host. However, looking at the coefficients, it seems that changing the price produces worse results than the case of no variation: Modality 1 (Increases >Decreases) has a coefficient of -10.47503 (C.I. 95% .833773 - 1.298233), Modality 2 (Increases < Decreases) has a coefficient of -22.67355 (C.I. 95% -26.23386 -19.11324) and Modality 3 (Increases=Decreases) has a coefficient of – 15.75118 (C.I. 95% .1466378 .6981545). Modality 1 seems the one with the least negative impact among the three, followed by Modality 3 and Modality 2. The difference of Modality 1 with the others, and its superiority, is also supported in the fixed effect model.

When the interaction with time is considered in the analysis, the p-value remains significant, in fact it is 0.000 (C.I. 95% .833773 1.298233), 0.000 (C.I. 95% .2728444 .8113811) and 0.003 (C.I. 95% .1466378 .6981545) respectively in the three modalities of price change, confirming that both in the short and long run changing the price has an impact on the ADR of the hosts, moreover, the negative coefficients decrease over time. The p-value here confirms the correctness of the adoption of a linear mixed effect model with random slope and random intercept.

Figure 15 illustrates the results of the analysis in this case.

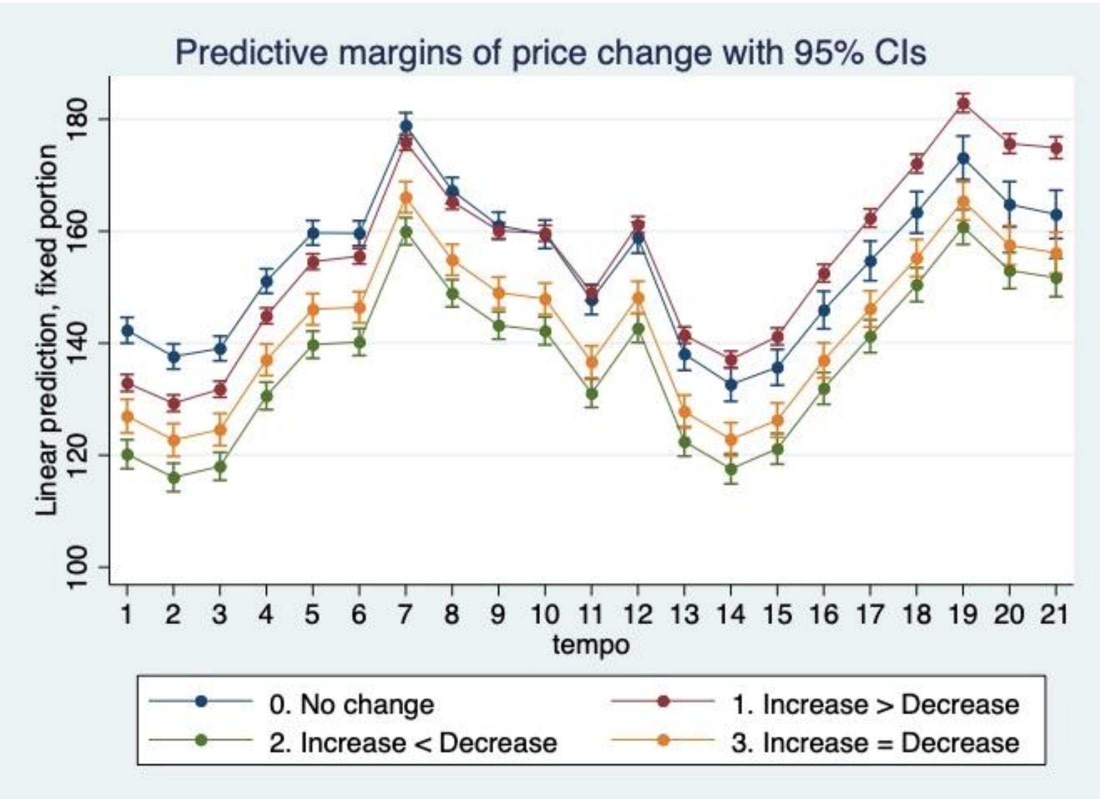

Figure 15 -Broken-line – Comparison of modalities

At time 1 (January 2016) performing no price change is the most profitable option, followed by Increase>Decrease, Increase=Decrease and Increase<Decrease. But after the peak at time 7 (July

2016) the difference between no change and Increase>Decrease lessens, and after time 10 (October 2016) Modality 1 results the most performing option.

The confounder of the analysis, tenure, has a p-value of 0.154 which indicates that this variable can't be considered to have a statistically significant impact on ADR. Moreover, it's negative coefficient (-0.4698582) (C.I. 95% -1.115966 .1762501) indicates that there is an inverse relationship between tenure and ADR, as the former increase, the latter is expected to decrease.

Observing the results of ADR- zip code, it appears that it has a statistically significant p-value (0.000) and a positive coefficient (0.9725248) (C.I. 95% .9669849 .9780647). This implies that the predictor has an impact on hosts' ADR, and there is a direct relationship between the two variables, they move in the same direction. Furthermore, they not only mode in the same direction, but as ADR zip increases of $1, the ADR per hosts increases of $0,9725.

4. Conclusions

4.1 Discussion and contribution to knowledge

Hypothesis 1a and 1b aimed at evaluating the impact of the dynamic pricing strategy applied in the context of the sharing economy, in the case of short-term accommodations rental. With the mixed effect model, the scenario of changing prices has been examined in two cases, that is, when time is included at its baseline level (i.e. January 2016) and when it is considered its progression, over a period of 21 months. In both cases the significant p-value obtained in the model confirms that changing prices has an impact on performance however, when we consider time at the initial stage, such impact is negative as illustrated by the negative coefficients.

As previous studies have observed, it is not always the case that AirBnB hosts have the technical and professional skills to understand how to use the dynamic pricing strategy properly and this could explain why this impact is negative (Gibbs et. al., 2018). When time progression is included, it can be observed that the negative impact of changing prices decreases over time and after 10 months, performing more price increases than decrease produces even a better result compared to the baseline scenario. The period examined is not long enough to affirm that the other two modalities will exhibit the same tendency, however, it is evident that the ADR increases over time also in the case in which hosts perform more decrease than increases or the same amount of them. The table below depicts the evolution of the ADR over the considered period.

	No change	Increases > Decreases	Increases = Decreases	Increases < Decreases
Jan-16	$ 46,06	$ 37,25	$ 31,33	$ 25,46
Feb-16	$ 46,06	$ 38,31	$ 31,75	$ 26,00
Mar-16	$ 46,06	$ 39,38	$ 32,17	$ 26,54
Apr-16	$ 46,06	$ 40,44	$ 32,59	$ 27,08
May-16	$ 46,06	$ 41,51	$ 33,01	$ 27,63
Jun-16	$ 46,06	$ 42,58	$ 33,44	$ 28,17
Jul-16	$ 46,06	$ 43,64	$ 33,86	$ 28,71
Aug-16	$ 46,06	$ 43,43	$ 33,00	$ 27,98
Sep-16	$ 46,06	$ 44,49	$ 33,43	$ 28,52
Oct-16	$ 46,06	$ 45,56	$ 33,85	$ 29,06
Nov-16	$ 46,06	$ 46,63	$ 34,27	$ 29,60
Dec-16	$ 46,06	$ 47,69	$ 34,69	$ 30,14
Jan-17	$ 46,06	$ 48,76	$ 35,12	$ 30,69
Feb-17	$ 46,06	$ 52,59	$ 35,54	$ 31,23
Mar-17	$ 46,06	$ 53,66	$ 38,73	$ 34,54
Apr-17	$ 46,06	$ 54,72	$ 39,15	$ 35,08
May-17	$ 46,06	$ 55,79	$ 39,57	$ 35,62
Jun-17	$ 46,06	$ 56,85	$ 39,99	$ 36,16
Jul-17	$ 46,06	$ 57,92	$ 40,42	$ 36,70
Aug-17	$ 46,06	$ 58,99	$ 40,84	$ 37,25
Sep-17	$ 46,06	$ 57,97	$ 41,26	$ 37,79

Table 8 - ADR evolution

It can be observed that in the short run (i.e. < 10 months) maintaining prices as fixed could be a reasonable action, this could be because hosts have time to build a customer base, receive reviews, build trust, and thereafter, are able to leverage on demand fluctuations to increase prices in their favor. However, after October 2016 Increasing prices more often than decreases is the most profitable strategy and this could be explained by the fact that if hosts manage to increase prices during peaks, they can maximize their revenues meeting consumers' willingness to pay. Hosts that prefer to attract lower spending guests or that for other reasons prefer to keep their rates low, could still take advantage of the dynamic pricing strategy by performing more price decreases than increases, or the same number of them because, as can be observed in the above table, in the long run all three modalities of price change show a positive trend. In fact, after 21 months, the average daily rates earned by hosts increase by 55,65%, 58,43% and 31,72% respectively.

The relationship between hosts' tenure, intended as the length of the subscription period in January 2016, and their ADR was tested through hypothesis 2. The p-value of 0.154 obtained through the mixed effect model analysis demonstrates that, in the case at hand, it can't be inferred that the more time a host has been subscribed, the better she understands how to use the dynamic pricing strategy to meet demand fluctuations and increase her profit. Li, Moreno & Zhang's (2015) research shows that in a year and a half 49% of previously available listing were no longer on the market. Based on this data, it seems that hosts that don't perform as expected, prefer to leave the market instead of adopting a different strategy, supporting the fact that time is not necessarily correlated to a better understanding of the market. The graph below summarizes the distribution of the observed population according to their tenure:

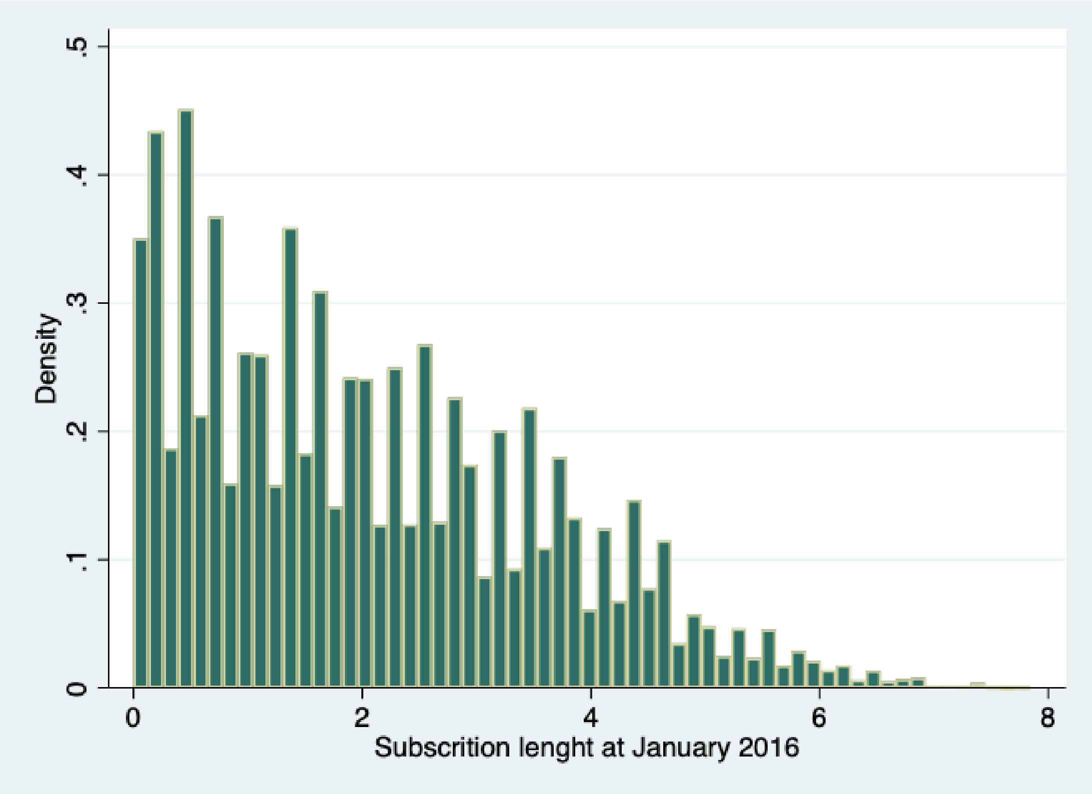

Figure 16 - Density vs Subscription length

It can be observed that 90% of the population included in the study, in January 2016 had been subscribed to AirBnB no longer than 4 years. Even though it is quite a considerable amount of time, it can be assumed that it is still not enough to properly understand the dynamics of such a complex environment. This result supports the findings of Li et al., (2025) research, in fact the density of the population gets lower the more the tenure increases, and it is reasonable to assume that after a certain period of time they leave the market. Moreover, even though price is the main determinant of consumer experience as it is the factor on which guests build expectations, hosts experience could be evaluated also considering hosts' self-marketing capabilities, and this could explain the absence of correlation between tenure and ADR in this study (Costello & Reczek, 2020).

In hypothesis 3, the ADR-zip was introduced in the model as a predictor, mainly to observe if location has an impact on price also for the accommodation-based sharing economy platforms and to understand if hosts can use the average daily rate of their neighborhood to set their prices, or if they make their choices only on the type of accommodation they are offering.

The results obtained with the mixed effect model, demonstrate that there is a direct relationship between ADR-zip code and ADR (p-value of 0.000). This confirms the fact that also in the context of sharing economy, the price of accommodation is influenced by location-based factors, in contrast

to what Wang & Nicolau (2017) affirm, in fact according to their research, accommodations' location does not have an impact on ADR in the sharing economy context.
Location-based factors, however, not only can be related to the proximity to popular areas, but also to specific characteristics of the area. Moreover, this information can be used by new platform joiners to set their daily rates considering those of their neighborhood competitors as a benchmark.

Employing the fixed effect model demonstrated that time has an impact on ADR and such impact differs across the modalities of price change. This result arouse the need and the curiosity to further investigate the relationship between the other variables and the evolution of the results over time.

This paper dived deep into the application of the dynamic pricing strategy in a relatively new and fast changing environment as the one of the digital platforms. It aimed at filling two main gaps: the first one being related to the application of dynamic pricing strategy by AirBnB hosts (*H1a* and *H1b*) and the second one about the relationship between tenure and pricing strategy (*H2*). With *H3* this study contributed to the existing insights about the aspects that sharing economy platforms in the hospitality sectors share with traditional incumbents.
It has demonstrated that in the long-run hosts can leverage on the dynamic pricing strategy to improve their performance and it has measured the impact of the modalities of price change on the average daily rate, demonstrating that there is a measurable difference between them and supporting Hypothesis *1a* and *1b*. Hosts have three modalities of price change with respect to keeping the price constant: perform more price increases than decreases; perform less price increases than decreases; and perform the same amount of price increases and decreases. These "sub-strategies" can be used in different contexts according to hosts' preferences.
Hosts could perform more price increases than decreases leveraging on peaks of high demand and leaving the price stable during the rest of the time, taking the risk of leaving unrented rent their accommodation in low demand times (if the price is too high with respect to their competitors), and in this scenario their efforts are concentrated only during the high demand peaks.
On the other hand, host that prefer to use themselves their assets during the peaks of high demand or that for any other reason prefer to focus on low demand periods, could put their efforts during those times trying to keep the accommodation rented by performing price decreases.
Whatever the case, these findings suggest that hosts can improve their performance if they apply the dynamic pricing strategy properly, demonstrating that this strategy is functional both for hotels and

for AirBnB hosts. Moreover, it highlights the fact that hosts could benefit from the aid of the smart pricing tools available on AirBnB.

Contrary to other findings (Abrate et al., 2022; Gibbs et al., 2018), this study suggests that when experience is considered as the subscription period, there is no direct relationship between it and the application of a correct pricing strategy, going against what inferred in Hypothesis 2. This means that it can't be inferred that hosts who have been subscribed for longer periods than other are more confident in using a dynamic pricing strategy, and hence it suggests that the learning curve for this type of activity may be long. Observing how the population is distributed between the classes of length of subscription period (Figure 16), there are relatively few users that have more than four years of experience and supporting Li et al. (2020) theory of hosts leaving the market. Moreover, the fact that the years of use of the platform do not directly impact the pricing strategy, further confirms that smart pricing tools can benefit platform users.

Lastly, the significant p-value of ADR zip-code supports Hypothesis *3,* and with this, this research demonstrates that there is a direct positive relationship between the average daily rate of individual hosts and the one of the neighborhoods. This result confirms that as it is the case for hotels, also the price of private accommodations is influenced by their location. Considering this, the paper supports what was observed by Gyodi & Nawaro (2021) and goes against the considerations of Wang & Nicolau (2017). Furthermore, knowing that the ADR of hosts is in line with that of their area, ADR zip-code, can help new and inexperience hosts in their pricing decisions, in fact, they could use it as a benchmark to set their rates and eventually try to follow the general pattern of this indicator.

4.2 Limitations and future research

The first limitation of this research comes from the data used. Those in fact were drawn by AirDNA, the source of AirBnB available listings, allowing for the analysis of pricing mechanism of only that platform. Since the advent of AirBnB, multiple other platforms were created offering the same or similar services, it could be interesting observing pricing dynamics and hosts' behaviors in these other platforms, some of them are eDreams.com, Bookings,com, Trip.com, Agoda, TripAdvisor and Expedia. Moreover, among the AirBnB competitors just mentioned, there are some (eDreams, for example) that list accommodations, hotels and flights. Considering that the dynamic pricing strategy is a tool that hotels and airlines employ, researchers could analyze how this strategy is managed in such variegated platforms.

As observed in the previous section, only the modality Increase>Decrease can be defined profitable in the long run, this is because it is evident that after 10 months it outpaces the others, however, it could be interesting observing how all the three modalities change over a longer period, as the one considered is not long enough to observe changes in the other modalities. Moreover, data show that the modality Decrease>Increase has a growth trend, even if it is slower than the other, would it be different if hosts publicize their discounts? Future research could analyze how the impact of the modalities of price change vary if marketing activities are performed. Ultimately, this paper highlighted that the three modalities have. Appositive growth trend but because of the short time period examined, it wasn't possible to derive a specific profitable pattern, this leaves the door open to further explore this concept and discover how these strategies can be used to maximize hosts' profits.

I analyzed the relationship between tenure and ADR considering hosts' tenure in January 2016 and the evolution over the 21 months observed was not monitored, how long does it take to inexperienced hosts to learn and use the dynamic pricing strategy? Is it correct to assume they leave the market if they don't achieve the expected results? Researchers could dive deep into these questions.
Furthermore, as mentioned earlier in this paper, most researchers have analyzed the relationship between hosts experience and ADR or profit only considering the number of listings per hosts as a proxy for their experience. Future research can follow the path I started and derive a learning curve for non-professional hosts on P2P platforms. Furthermore, hosts' experience has been evaluated in terms of number of listings and subscription period, however, there can be other measures of experience that influence the success or failure of available listings, some of them can be hosts' ability to manage communications with their clients or to choose the right pictures and accommodation descriptions. Exploring the different facets and consequent implications of hosts experience can contribute to existing literature.

Lastly, this paper takes a stand towards Gyodi & Nawaro (2021) study according to which the location of private accommodations has an impact on the ADR of hosts. However, the discrepancy between these results and those of Wang & Nicolau (2017) is a topic that worth further investigation.

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Summary

Abstract

The traditional hospitality industry has undergone significant changes since the advent of sharing economy platforms such as AirBnB, which have redefined the competitive landscape (Gibbs, Guttentag, Gretzel, Yao & Morton, 2018). Despite the differences between platforms and traditional accommodation providers, they share the use of the same profit maximization tool: the dynamic pricing strategy. This strategy is rather simple and requires data analysis skills, on one side hotels have trained professionals that implement it, on the other there are users with different cultural backgrounds, skills, and purposes (Gibbs et al., 2018). Understanding the dynamics of such strategy would help non-professional users to maximize their profits, and it would ultimately positively impact the platform itself because of the network effects.

This study is built on the test of three hypothesis that aim at understanding the interplay between the dynamic pricing strategy and two main variables, the hosts average daily rates and their tenure (intended as the subscription time at the beginning of the study). To deepen the understanding of the dynamics underlying such complex strategy, a difference between the modalities of price change has been done, and its effects analyzed. The hypotheses were tested using data about AirBnB listings over a period of 21 months for over 1 million observations. The analysis was conducted using a Linear Fixed Effect and a Mixed Effect model applied to longitudinal data.

The research demonstrates that using the dynamic pricing strategy is profitable also in the sharing economy platform environment, however, the modalities of price change have different impacts and timing. Despite the differences between them, they all result to be profitable in the long run. There is no evidence of a relationship between hosts' tenure and their ability to impact their ADR using the dynamic pricing strategy, it appears that the learning curve in such a complex environment is quite long. Furthermore, this study generates insights about the correlation between the average daily rates of listings belonging to the same zip code and the one of individual hosts. Contrary to other findings (Wang & Nicolau, 2017), results demonstrate that the average daily rate of the area influences the one charged by hosts, signaling that hosts can use it as a benchmark for their rates. Moreover, this evidence demonstrates that location is an influencing factor in this environment, as it is for the traditional hospitality industry.

Research rationale & Conceptual model

One of the major players within the sharing economy is AirBnB which has been defined a disruptive innovator and has built its competitive advantage on an asset-light business model. The platform was launched in 2008 and today its market share accounts for 20% of the vacation rental industry (Akbar & Tracogna, 2018). The entrance of this innovative accommodation provider has impacted traditional incumbents' performance: 50% of actual AirBnB users prefer its offerings over those of hotels, moreover, the platform is from 6% to 18% cheaper than hotels (Zervas et al., 2017). Because of the significant implications related to this entrant, researchers have investigated multiple aspects of the phenomenon, some of these are the factors that drive consumers' adoption of the sharing economy (Kumar, Jha, Damodaran, Bangwal & Dwivedi 2020; Liu & Yang, 2018; Yi, Yuan & Yoo, 2020), the impact that AirBnB has had on the pricing strategy of hotels (Li & Srinivasan, 2018; Gibbs, Guttentag, Gretzel, Yao & Morton, 2018), the impact of the disruptive platform on hotels' sales growth (Blal, Singal & Templin, 2018), or the relationship between reviews and price setting on online platforms, using AirBnB data to draw a sentiment analysis (Lawani, Reed Mark & Zheng, 2019).

Two main gaps were identified: the first one is related to the use and effectiveness of the dynamic pricing strategy applied by AirBnB hosts, the second one concerns the relationship between hosts' experience and their ability to implement an effective dynamic pricing strategy. There are multiple researches focused on the effectiveness of the dynamic pricing strategy, however these consider the strategy within the traditional accommodation sector and the airline industry, which was the first one to adopt such peculiar strategy, However, there are discordant opinions concerning the similarities between the sharing economy environment and that of hotels. Despite the two share some similarities, they are different, and it is because of this differences that it is worth to examine the above-mentioned factors within this specific environment.

The accommodation sector is characterized by perishability, demand volatility and advanced bookings, factors that give it the perfect fit with a dynamic pricing strategy, which consists in adjusting prices according to fluctuations in demand and other contextual factors (Gibbs et al., 2017; Abrate, Sainaghi & Mauri, 2022). Hotels widely use this strategic revenue management tool, as they have trained professionals that analyze past records, make predictions of demand fluctuations and set prices, but very often listings on AirBnB belong to non-professionals hosts that seek to make extra profits from their underutilized resources, and as demonstrated by Li, Moreno & Zhang (2015), they hardly ever use a dynamic pricing strategy. In fact, from their research it appears that non-professional hosts set their price when they list their accommodation and don't respond to fluctuations in demand, making an average daily revenue and an occupancy rate of 16,9% and 15,5% respectively lower than professional hosts (Li et al., 2015). The consequence of these results is that hosts that don't see the revenues they expected, may prefer to leave the market, and this in turns negatively impacts the platform. In fact, as a two-sided market, it is influenced by network externalities, meaning that as the user-base decreases the value users can derive also decreases (Li et al., 2015; Goldenberg, Libai & Muller, 2010). In light of this evidence, it is relevant understanding the impact that applying the dynamic pricing strategy can have on hosts' profits, and this will be tested through the following hypothesis:

H1a: Hosts adopting a dynamic pricing strategy have a better performance than those that don't.

Price is a key factor in consumers' decisions, it appears in fact that consumers tend to make a direct correlation between the price they pay and the quality they expect to receive, and price is the main variable that affects consumers' experience (Magno, Cassia & Ugolini, 2017; Pappas, 2019). Considering this, hosts should carefully decide the range of price change to avoid incurring two major risks: pricing their accommodations too high could make them lose potential medium spending guests, whereas pricing them too low could make their listings be perceived as low-quality ones. Lee & Deale (2021) found out that when prices are too low compared to similar listings in the same location, consumers' risk perception increases as well as a lack of trust. Pappas (2019) in his study highlights the fact that prices highly influence purchasing decisions of consumers, and he reiterates the fact that consumers use it to evaluate product superiority or excellence. These findings highlight the need of understanding the difference between the modalities of price change, therefore the following hypothesis is formulated:

H1b: It can be identified a difference in impact in the modalities of price change.

As aforementioned, hotels rely on trained professionals to manage their pricing strategy, which is a time consuming and data-driven activity that allows to forecast demand and seasonality (Abrate, Sainaghi & Mauri, 2022). Various researches have observed the interplay between experience and the use (and effectiveness) of the dynamic pricing strategy, however, the majority of them have considered the number of hosts' listings as a proxy for their experience. In this study instead, it will be investigated the impact that the length of the subscription period has on hosts' performance, to evaluate a potential learning curve, therefore hypothesis 2 will be tested:

H2: Tenure is a confounder for the association between hosts' performance and dynamic pricing strategy.

There are contrasting opining concerning the similarities between this new accommodation sector and the traditional one, and specifically the factors that impact pricing decisions. Napierala & Lesniewska (2014) considered location-based factors as the main forces influencing the price that structures can charge, Wang and Nicolau (2017) instead argue that in the case of AirBnB the location cannot be considered a major determinant. Listings located in the same area, however, share latent characteristics other than their proximity to specific attractions, these could be neighbors' acceptance of tourism activities and the continuous flow of people in their building, or if the area is safe at night (Pappas, 2019), and if these have impact on price, it could be reasonable to develop the following hypothesis:

H3: Hosts' profits are correlated to average daily rate of their zip-code.

Dataset and variables

Data used to test the hypothesis were collected from previous research. Such data were drawn by AirDNA, considered one of the most comprehensive sources of AirBnB listings. The data set in fact included information about Airbnb listings in the state of California (US) for 20 months, from January 2016 to September 2017. The initial dataset included over 7 million observations and 33 variables, and it has gradually been reduced to keep only the variables and observations relevant for the purpose of this study (1.030.934 observations and 11 variables), these were chosen following the reasoning illustrated by the following DAG:

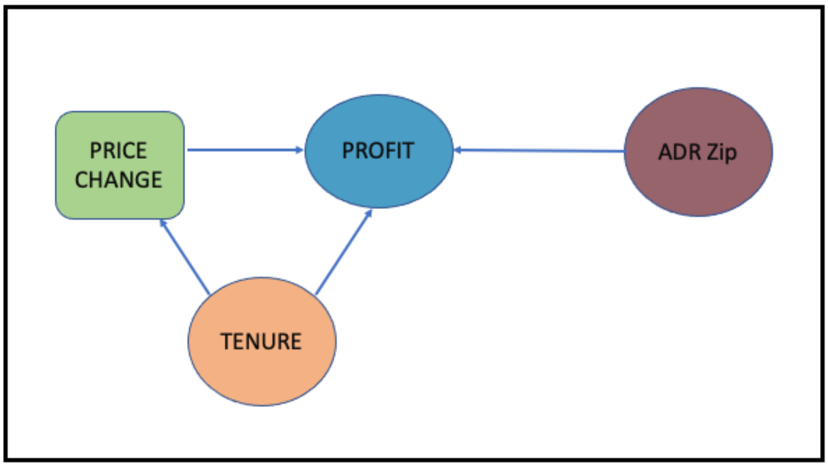

Figure 17 - Causal DAG

The table below summarizes the variables and measures used to conduct the analysis.

Variables	Description	Measure
ADR	Dependent variable	Proxy of hosts' monthly performance
Price change	Independent variable: Exposure	Propensity to change the price over observed time
ADR per zip-code	Independent variable: Predictor	Proxy of monthly performance per address zone
Tenure	Independent variable: Confounder	Hosts' experience as for January 2016

Table 9- Variables

ADR is the proxy used to measure hosts' monthly performance in terms of profit, it is a function of price per night, number of rented rooms over available rooms and number of nights per rented room, and it was already available when the initial dataset was downloaded.

The exposure, price change, in the initial dataset was classified into three different sub-variables, total number of price changes, number of price increases and number of price decreases. However, to measure the tendency to take on a dynamic pricing strategy, the three modalities just mentioned, were used to create a categorical variable with four modalities:

0. No price change: the host has never changed the price over time.
1. Increases > Decreases: the host has performed more price increases than decreases.
2. Increases < Decreases: the host has performed less price increases than decreases.
3. Increases = Decreases: the host has performed the same number of price increases and decreases.

This variable was created with the intention to measure the difference in impact of price increases and/or decreases.

Tenure, is used as a proxy for the level of experience that hosts have and it represent the subscription time of hosts at the beginning of the study (January 2016) and lastly, ADR per zip code, is the independent variable that indicates the average revenue of the neighborhood, and it has been included to observe if and, eventually, how much, it influences hosts' profit.

Analysis

The data available in this study are longitudinal, this means that repeated measurements are conducted on each individual over short or long periods of time to observe fluctuations in behavior, emotions or health status. Because it is not always intuitive understating the dependence or independence of certain variables researchers may incur the risk of applying the wrong model, to avoid this risk and to have a deeper understanding of the relationship between the variables, both fixed-effects and mixed-effects model were applied (Clark & Linzer, 2014).

The main difference between the two models concerns what is believed about the values of the independent variable: when the values of the independent variables are estimated to be fixed, the main assumption is that they represent the entire population of interest and there are no other relevant factors to examine, and the model to use is the fixed-effect model, when instead the values of an independent variable are believed to be drawn at random from a larger population, it is more appropriate to use a mixed-effects model.

Results

The two tables below summarize the main results from the fixed-effects model and the mixed-effects one respectively:

ADR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
time	.4175169	.0215805	19.35	0.000	.3752198	.4598139
change						
1. increase>decrease	0	(omitted)				
2. increase<decrease	0	(omitted)				
3. increase=decrease	0	(omitted)				
adr_zipM	0	(omitted)				
exp	0	(omitted)				
_cons	40.48734	.3962727	102.17	0.000	39.71066	41.26403

Table 10 The Fixed effects model

ADR.	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
timesp1	.0917319	.114567	0.80	0.423	-.1328153	.3162791
timesp2	-1.186397	.1501055	-7.90	0.000	-1.480599	-.8921957
timesp3	1.579639	1.11104	1.42	0.155	-.5979587	3.757237
Change						
1. increase>decrease	-10.47503	1.448446	-7.23	0.000	-13.31393	-7.636125
2. increase<decrease	-22.67355	1.816517	-12.48	0.000	-26.23386	-19.11324
3. increase=decrease	-15.75118	1.981748	-7.95	0.000	-19.63533	-11.86702
time	0	(omitted)				
cambio#c.time						
1. increase>decrease	1.066003	.1184868	9.00	0.000	.833773	1.298233
2. increase<decrease	.5421128	.1373844	3.95	0.000	.2728444	.8113811
3. increase=decrease	.4223962	.1406956	3.00	0.003	.1466378	.6981545
adr_zipM	.9725248	.0028266	344.07	0.000	.9669849	.9780647
exp	-.4698582	.3296531	-1.43	0.154	-1.115966	.1762501
_cons	46.05967	1.353695	34.03	0.000	43.40648	48.71286

Table 11 - The LMM

This fixed effect model analyzes the effect of time, the other variables are excluded from the analysis as they are time variant factors. In Table 2 it can be observed that the coefficient of time is positive and statistically significant (coeff. 0.4175169; p-value 0.000; C.I.: 0.3752198 – 0.4598139), this means that with respect to the baseline level of 40.5$, the ADR of hosts increases of an amount equal to 0.42$. To observe how the modalities of price change interact with time, the above model has been deepened, and the effect of time has been analyzed in the four modalities of price change. What came out is that when hosts perform no price change or the same number of increases and decreases, the effect of time is not statistically significant, contrary to what results in the other two scenarios. From this model it can be inferred that modality 1 is the most profitable one. Since from this model emerges that time is a statistically significant factor, the mixed effects model can provide further evidence.

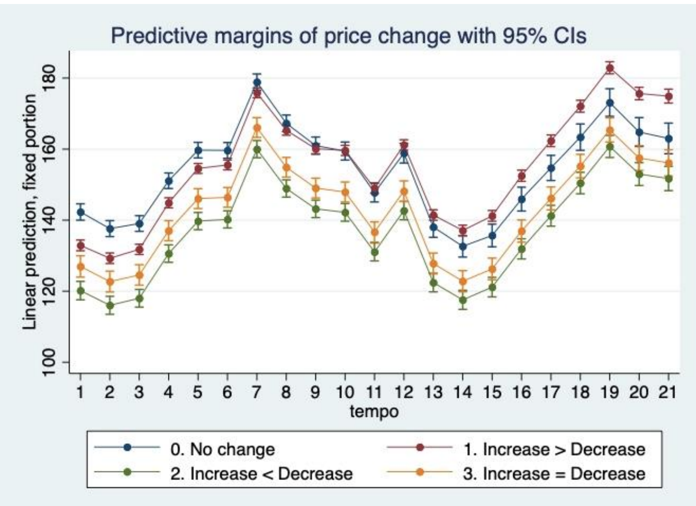

Figure 18 -Broken-line – Comparison of modalities

According to the results of the mixed effects model illustrated in Table 7, over time Modality 1 is the most profitable one, as highlighted also in the fixed effects model. In Figure 15 it is observed the trend that the modalities follow overtime: Modality 2 is the least performing one, followed by Modality 3. After 10 months since the beginning of the analyzed period, Modality 1 becomes the most profitable one, outpacing Modality 0.

Tenure has a p-value of 0.154 which indicates that this variable can't be considered to have a statistically significant impact on ADR.

ADR- zip code has a statistically significant p-value (0.000) and a positive coefficient (0.9725248) (C.I. 95% .9669849 .9780647). This implies that it has an impact on hosts' ADR, and there is a direct relationship between the two variables, they move in the same direction.

Discussion and contribution to knowledge

Hypothesis 1a and 1b aimed at evaluating the impact of the dynamic pricing strategy applied in the context of the sharing economy, in the case of short-term accommodations rental. With the mixed effect model, the scenario of changing prices has been examined in two cases, that is, when time is included at its baseline level (i.e. January 2016) and when it is considered its progression, over a period of 21 months. In both cases the significant p-value obtained in the model confirms that changing prices has an impact on performance however, when we consider time at the initial stage, such impact is negative as illustrated by the negative coefficients.

As previous studies have observed, it is not always the case that AirBnB hosts have the technical and professional skills to understand how to use the dynamic pricing strategy properly and this could explain why this impact is negative (Gibbs et. al., 2018). When time progression is included, it can be observed that the negative impact of changing prices decreases over time and after 10 months, performing more price increases than decrease produces even a better result compared to the baseline scenario. The period examined is not long enough to affirm that the other two modalities will exhibit the same tendency, however, it is evident that the ADR increases over time also in the case in which hosts perform more decrease than increases or the same amount of them. The table below depicts the evolution of the ADR over the considered period.

	No change	Increases > Decreases	Increases = Decreases	Increases < Decreases
Jan-16	$ 46,06	$ 37,25	$ 31,33	$ 25,46
Feb-16	$ 46,06	$ 38,31	$ 31,75	$ 26,00
Mar-16	$ 46,06	$ 39,38	$ 32,17	$ 26,54
Apr-16	$ 46,06	$ 40,44	$ 32,59	$ 27,08
May-16	$ 46,06	$ 41,51	$ 33,01	$ 27,63
Jun-16	$ 46,06	$ 42,58	$ 33,44	$ 28,17
Jul-16	$ 46,06	$ 43,64	$ 33,86	$ 28,71
Aug-16	$ 46,06	$ 43,43	$ 33,00	$ 27,98
Sep-16	$ 46,06	$ 44,49	$ 33,43	$ 28,52
Oct-16	$ 46,06	$ 45,56	$ 33,85	$ 29,06
Nov-16	$ 46,06	$ 46,63	$ 34,27	$ 29,60
Dec-16	$ 46,06	$ 47,69	$ 34,69	$ 30,14
Jan-17	$ 46,06	$ 48,76	$ 35,12	$ 30,69
Feb-17	$ 46,06	$ 52,59	$ 35,54	$ 31,23
Mar-17	$ 46,06	$ 53,66	$ 38,73	$ 34,54
Apr-17	$ 46,06	$ 54,72	$ 39,15	$ 35,08
May-17	$ 46,06	$ 55,79	$ 39,57	$ 35,62
Jun-17	$ 46,06	$ 56,85	$ 39,99	$ 36,16
Jul-17	$ 46,06	$ 57,92	$ 40,42	$ 36,70
Aug-17	$ 46,06	$ 58,99	$ 40,84	$ 37,25
Sep-17	$ 46,06	$ 57,97	$ 41,26	$ 37,79

Table 12 - ADR evolution

It can be observed that in the short run (i.e. < 10 months) maintaining prices as fixed could be a reasonable action, this could be because hosts have time to build a customer base, receive reviews, build trust, and thereafter, are able to leverage on demand fluctuations to increase prices in their favor. However, after October 2016 Increasing prices more often than decreases is the most profitable strategy and this could be explained by the fact that if hosts manage to increase prices during peaks, they can maximize their revenues meeting consumers' willingness to pay. Hosts that prefer to attract lower spending guests or that for other reasons prefer to keep their rates low, could still take advantage of the dynamic pricing strategy by performing more price decreases than increases, or the same number of them because, as can be observed in the above table, in the long run all three modalities of price change show a positive trend. In fact, after 21 months, the average daily rates earned by hosts increase by 55,65%, 58,43% and 31,72% respectively.

The relationship between hosts' tenure, intended as the length of the subscription period in January 2016, and their ADR was tested through hypothesis 2. The p-value of 0.154 obtained through the mixed effect model analysis demonstrates that, in the case at hand, it can't be inferred that the more time a host has been subscribed, the better she understands how to use the dynamic pricing strategy to meet demand fluctuations and increase her profit. Li, Moreno & Zhang's (2015) research shows that in a year and a half 49% of previously available listing were no longer on the market. Based on this data, it seems that hosts that don't perform as expected, prefer to leave the market instead of adopting a different strategy, supporting the fact that time is not necessarily correlated to a better understanding of the market. The graph below summarizes the distribution of the observed population according to their tenure:

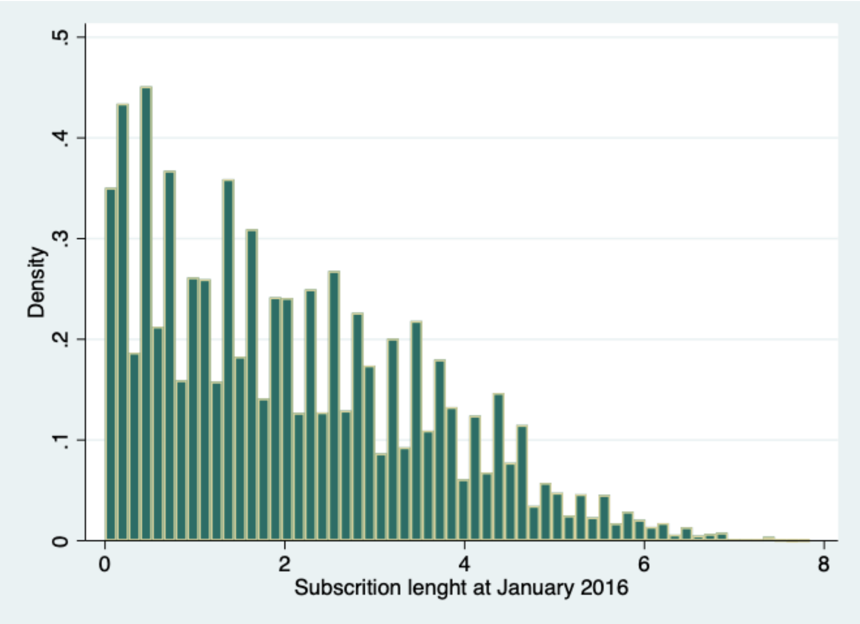

Figure 19 - Density vs Subscription length

It can be observed that 90% of the population included in the study, in January 2016 had been subscribed to AirBnB no longer than 4 years. Even though it is quite a considerable amount of time, it can be assumed that it is still not enough to properly understand the dynamics of such a complex environment. This result supports the findings of Li et al., (2025) research, in fact the density of the population gets lower the more the tenure increases, and it is reasonable to assume that after a certain period of time they leave the market. Moreover, even though price is the main determinant of consumer experience as it is the factor on which guests build expectations, hosts experience could be evaluated also considering hosts' self-marketing capabilities, and this could explain the absence of correlation between tenure and ADR in this study (Costello & Reczek, 2020).

In hypothesis 3, the ADR-zip was introduced in the model as a predictor, mainly to observe if location has an impact on price also for the accommodation-based sharing economy platforms and to understand if hosts can use the average daily rate of their neighborhood to set their prices, or if they make their choices only on the type of accommodation they are offering.
The results obtained with the mixed effect model, demonstrate that there is a direct relationship between ADR-zip code and ADR (p-value of 0.000). This confirms the fact that also in the context of sharing economy, the price of accommodation is influenced by location-based factors, in contrast to what Wang & Nicolau (2017) affirm, in fact according to their research, accommodations' location does not have an impact on ADR in the sharing economy context.
Location-based factors, however, not only can be related to the proximity to popular areas, but also to specific characteristics of the area. Moreover, this information can be used by new platform joiners to set their daily rates considering those of their neighborhood competitors as a benchmark.

Employing the fixed effect model demonstrated that time has an impact on ADR and such impact differs across the modalities of price change. This result arouse the need and the curiosity to further investigate the relationship between the other variables and the evolution of the results over time.

This paper dived deep into the application of the dynamic pricing strategy in a relatively new and fast changing environment as the one of the digital platforms. It aimed at filling two main gaps: the first one being related to the application of dynamic pricing strategy by AirBnB hosts (*H1a* and *H1b*) and the second one about the relationship between tenure and pricing strategy (*H2*). With *H3* this study contributed to the existing insights about the aspects that sharing economy platforms in the hospitality sectors share with traditional incumbents.
It has demonstrated that in the long-run hosts can leverage on the dynamic pricing strategy to improve their performance and it has measured the impact of the modalities of price change on the average

daily rate, demonstrating that there is a measurable difference between them and supporting Hypothesis *1a* and *1b*. Hosts have three modalities of price change with respect to keeping the price constant: perform more price increases than decreases; perform less price increases than decreases; and perform the same amount of price increases and decreases. These "sub-strategies" can be used in different contexts according to hosts' preferences.

Hosts could perform more price increases than decreases leveraging on peaks of high demand and leaving the price stable during the rest of the time, taking the risk of leaving unrented rent their accommodation in low demand times (if the price is too high with respect to their competitors), and in this scenario their efforts are concentrated only during the high demand peaks.

On the other hand, host that prefer to use themselves their assets during the peaks of high demand or that for any other reason prefer to focus on low demand periods, could put their efforts during those times trying to keep the accommodation rented by performing price decreases.

Whatever the case, these findings suggest that hosts can improve their performance if they apply the dynamic pricing strategy properly, demonstrating that this strategy is functional both for hotels and for AirBnB hosts. Moreover, it highlights the fact that hosts could benefit from the aid of the smart pricing tools available on AirBnB.

Contrary to other findings (Abrate et al., 2022; Gibbs et al., 2018), this study suggests that when experience is considered as the subscription period, there is no direct relationship between it and the application of a correct pricing strategy, going against what inferred in Hypothesis 2. This means that it can't be inferred that hosts who have been subscribed for longer periods than other are more confident in using a dynamic pricing strategy, and hence it suggests that the learning curve for this type of activity may be long. Observing how the population is distributed between the classes of length of subscription period (Figure 16), there are relatively few users that have more than four years of experience and supporting Li et al. (2020) theory of hosts leaving the market. Moreover, the fact that the years of use of the platform do not directly impact the pricing strategy, further confirms that smart pricing tools can benefit platform users.

Lastly, the significant p-value of ADR zip-code supports Hypothesis *3*, and with this, this research demonstrates that there is a direct positive relationship between the average daily rate of individual hosts and the one of the neighborhoods. This result confirms that as it is the case for hotels, also the price of private accommodations is influenced by their location. Considering this, the paper supports what was observed by Gyodi & Nawaro (2021) and goes against the considerations of Wang & Nicolau (2017). Furthermore, knowing that the ADR of hosts is in line with that of their area, ADR zip-code, can help new and inexperience hosts in their pricing decisions, in fact, they could use it as a benchmark to set their rates and eventually try to follow the general pattern of this indicator.