Sharing economy and dynamic pricing: Is the impact of Airbnb on the hotel industry time-dependent?

Abstract

Prior literature has reported significant price and revenue reductions in the hotel industry due to the emergence of Airbnb. Other studies have documented that hotels' price reactions to the penetration of Airbnb depend on their service level, e.g., low/medium-end versus high end. Relying on a large sample from the Italian market, we contribute by showing that the effect of Airbnb on hotels' price decisions does not only depend on incumbents' quality level, but also on the difference between booking and check-in time. That is, the effect of the penetration of Airbnb on hotels' dynamic price decisions varies over time depending on the core segment hotels target.

Keywords: Sharing Economy, Pricing, Revenue Management, Hospitality Industry, Empirical Analysis.

1. Introduction

The sharing economy phenomenon has emerged in a number of different sectors (e.g., hospitality, car transportation service) by virtue of Internet-based platforms enabling peer-to-peer sharing of resources owned by individuals upon payment. As such, sharing economy platforms represent an effective alternative channel to access goods and services traditionally provided by long-established industries (Belk, 2014; Sundararajan, 2016; Jiang and Tian, 2018; Dolnicar, 2019). The main strength of sharing economy platforms is the ability to offer *very competitive prices* for goods and services (Roma et al., 2019). This feature is due to the low barriers to entry characterizing these platforms, which incentivize a plethora of individuals, including people with very low opportunity cost, to offer their underutilized resources (Karlsson and Dolnicar, 2016). Indeed, the resources offered on sharing economy platforms are usually purchased for other scopes (e.g., private consumption), and therefore they can generate extra-income without additional costs, thus reducing prices (Benkler, 2004; Blal et al., 2018; Roma et al., 2019). This naturally confers to sharing economy platforms an important competitive advantage of cost leadership over traditional incumbents (Zervas et al., 2017; Guttentag et al., 2018), which makes them a serious competitive threat especially in industries characterized by high variability in consumers' demand (Zervas et al., 2017). This is also due to the unique characteristic of sharing economy players of being able to easily scale supply to meet demand by relying on a multitude of geographically distributed resources (Einav et al., 2016; Zervas et al., 2017; Li and Srinivasan, 2019).

To clarify, consider for instance the case of sharing economy players in the hospitality industry. In the short-run, resource owners (i.e., hosts) operating on peer-to-peer platforms (e.g., Airbnb) can decide whether to host on a particular date, and reasonably, they will be more likely to host travelers when prices or demand are relatively high, while using accommodation for other scopes (e.g., private usage) when prices or demand are low. By virtue of the flexible nature of the supply of resources' owners, sharing economy platforms can be highly responsive to fluctuations in demand, as compared to hotels. The latter are indeed less able to quickly expand (or reduce) capacity during positive (negative) peaks in demand because of their fixed capacity in the short term.

In light of the increasing importance of sharing economy players, a number of scholars have started studying how sharing economy entry influences incumbents' reactions. The majority of these studies are related to the hospitality industry, as this industry exemplifies the setting where the sharing economy is having the biggest impact due to the presence of Airbnb (Blal et al., 2018; Guttentag, 2015; Guttentag and Smith, 2017; Volgger et al., 2019; Zach et al., 2020; Voltes-Dorta and Sanchez-Medina, 2020). However, only few empirical works have studied the effect of new sharing economy entry on incumbents' *pricing decisions* (e.g., Neeser, 2015; Lane e Woodworth, 2016; Roma et al., 2019; Zervas et al., 2017). In particular, these studies have found a negative effect of sharing economy players' presence on incumbents' prices (i.e., hotel prices), although this effect may hinge upon other factors, such as the quality level of the incumbents or the purpose of accommodation (Zervas et al., 2017; Roma et al., 2019).

The investigation of how the presence of a sharing economy player affects the *dynamic pricing decisions* of incumbents has been quite surprisingly overlooked. That is, scant attention has been devoted to the study of how the *time factor* may moderate the effect of the presence of a sharing economy player on incumbents' price decisions, even though it would represent an important advancement to the extant literature. In fact, to the best of our knowledge, it is still unclear how the emergence of a disruptive business model with such high flexibility in matching supply and demand would affect the way incumbents *dynamically* adjust their prices over time to sell their capacity and fulfill demand. Unraveling this issue is pivotal to firms operating in industries where the practice of dynamic pricing is very common due to the presence of high demand uncertainty and fixed capacity in the short term (PK and Praveen, 2001).

We fill the above gap by focusing on hospitality industry and arguing that sharing economy's penetration (exemplified by Airbnb's penetration) in this industry exerts a time-dependent impact on the dynamic pricing policy of hotels, which differs depending on their quality level (high-end vs. low/medium-end hotels). Specifically, due to a direct competition effect, per Roma et al. (2019)'s intuitions, we suggest that low/medium-end hotels (e.g., 1-3 star hotels) naturally set lower average price in geographical areas where Airbnb's penetration is higher, as compared with areas less penetrated by Airbnb.

More importantly, we contribute by adding that this price gap may increase or decrease over time. On the one hand, the price gap may be amplified as the accommodation date approaches. That is, the negative effect of Airbnb on low/medium-end hotels' price may be stronger when booking very close to the accommodation date because the flexible nature of the sharing economy should lead this type of supply (e.g., Airbnb hosts' rooms/houses) to become available and more competitive when demand conditions become clearer. On the other hand, it is also possible that the price gap may be higher far from the accommodation date and actually decrease over time. This could be explained by the purchasing behavior of consumers typically attracted by sharing economy platforms, i.e., price-conscious consumers purchasing for leisure purposes (e.g., vacation).[1] Such consumers are more likely to book their accommodations long before the accommodation date to save money, given that they normally expect an increase in average prices over time. As a consequence, competition from Airbnb may be stronger early in advance

[1] It has been indeed observed that the great majority (even 90%) of travelers attracted by sharing economy platforms such as Airbnb are leisure travelers, who are typically more price sensitive (Li and Srinivasan, 2019; Roma et al., 2019).

rather than close to the accommodation date in order to match the characteristics of this type of consumers. Moving to high-end hotels (e.g., 4-5 star hotels), we argue that they set higher prices in geographical areas where Airbnb's penetration is higher, as compared with areas where Airbnb's penetration is milder. More importantly, we advance that this price gap should be stable, irrespective of whether service booking occurs early in advance or close to the service consumption date. This is because high-end hotels need to maintain positioning consistency over time.

To test our arguments, we rely on a unique dataset encompassing more than 150,000 price offerings available on Booking.com website (starting three months until one week before the accommodation date) and related to weekend accommodation search from more than 3,000 hotels located in top visited cities in Italy. By way of anticipation, our findings suggest that, as supposed, incumbents' price reactions to sharing economy entry vary *over time* differently depending on the quality level of the incumbents. Specifically, we find that hotels targeting low/medium-end consumer segments (i.e., 1-3 star hotels) tend to set lower prices in cities where sharing economy (i.e., Airbnb) has a higher penetration, compared to cities where sharing economy has lower penetration. More importantly, this negative price gap *decreases* as the accommodation date is approached. Quite interestingly, this suggests that the role of the type of consumers attracted by sharing economy platforms is more prevalent that the discussed effect of the flexible nature of sharing economy supply. On the contrary, due to positioning coherency reasons, we find no evidence that the positive relationship between Airbnb's penetration and high-end hotels' prices varies *over time*.

We contribute on the nascent literature on the sharing economy as well as on the extant literature on incumbents' pricing reactions to new entries, by demonstrating that these reactions may or may not change as the service consumption date gets closer depending on the type of service quality offered. From a managerial viewpoint, our results suggest incumbents in the hospitality industry to pay attention on sharing economy penetration in their specific geographical area, since sharing economy represents a strong threat for them depending on the type of incumbents (low/medium-end vs. high-end) and, interestingly, on the temporal distance from the service consumption date. Our study has also implications for consumers and policy makers. Indeed, the different dynamic pricing decisions pursued by 1-3 star hotels and 4-5 star hotels as a consequence of the different Airbnb' penetration implies that the higher or lower penetration of the sharing economy will influence prices of all the alternative accommodation services in a given geographical area, as well as how they will change over time. In turn, this will unavoidably affect consumers' options. Finally, although our study refers to a pre-COVID-19 period, we also discuss the possible implications of COVID-19 pandemic on our findings, due to its relevance for the future of sharing economy in the hospitality industry.

The remainder of the paper unfolds as follows. In Section 2 we propose our arguments and formulate the relative hypotheses. In Section 3, we describe the data, the variables and the methods utilized in this paper. In Section 4, we present and discuss our findings. In Section 5, we show robustness of findings under different model specifications. Finally, in Section 6 we conclude by providing managerial implications and discussing avenues for future research.

2. Theoretical background and hypotheses

2.1 Literature background on sharing economy

Due the growing relevance of the sharing economy in the hospitality industry, there has been a proliferation of studies trying to shed light on a number of issues related to this phenomenon, such as host pricing strategies (Gibbs et al., 2018a, 2018b; Voltes-Dorta and Sanchez-Medina, 2020), hosts-guests relationships (Casais et al., 2020; Apostolidis and Brown, 2021), trust, reputation, brand loyalty, and various antecedents and consequences of consumer behavior in sharing economy platforms (e.g., Ert et al., 2016, 2019; Benoit et al., 2017; Liang et al., 2018; Lutz and Newlands, 2018; Mahadevan, 2018; Abrate and Viglia, 2019; Ert et al., 2019; Mody et al., 2019; Mao et al., 2020; Mody and Hanks, 2020; Suess et al., 2020; Xie et al., 2020; Xu and Gursoy, 2020; Xu et al., 2020; Lim et al., 2021; Pitt et al., 2021). Other studies have examined sharing economy regulation issues (Grimmer et al., 2019; Yang and Zhenxing, 2020; Yeon et al., 2020), as well as the effects of sharing economy entry on incumbents' profitability, survival, employment, and ability to secure investments (Zervas et al., 2015; Neeser, 2015; Fang et al., 2016; Zervas et al., 2017; Dogru et al., 2017; Hajibaba and Dolnicar, 2017; Blal et al., 2018; Heo et al., 2019; Li and Srinivasan, 2019; de Lange and Valliere, 2020; Dogru et al., 2020; Dogru et al., 2020; Sainaghi and Baggio, 2020; Maté-Sanchez-Val, 2020), ,

Besides a theoretical body of literature on sharing economy (Jiang and Tian, 2019; Li et al., 2020; Wang et al., 2020), very few studies have empirically examined the effect of sharing economy (i.e., Airbnb) on hotels' pricing policies. For instance, Zervas et al. (2015, 2017) have empirically analyzed the hospitality industry in Texas, finding that a higher penetration of sharing economy players reduces hotels' prices and revenues. Moreover, they have highlighted that such negative impact increases as the quality level of the hotel (i.e., the star category) decreases, thus confirming the substitution effect exerted by sharing economy players mostly on low/medium-end hotels. Similarly, Neeser (2015) has found that in Scandinavian countries sharing economy's penetration negatively influences hotels' daily average prices, although no impact is documented on hotels' revenue. In the same vein, Lane e Woodworth (2016) have empirically examined US hotels, finding that Airbnb exerts a negative impact on hotels' prices and such impact is greater in peak periods (i.e., high demand periods). Finally, more closely related to our paper, Roma et al. (2019) have revealed that sharing economy's impact on hotels' prices depends on the hotels' quality level as well as on their offer characteristics, in a nontrivial manner. Specifically, while this impact results in lower prices for low/medium-end hotels, it yields higher prices for high-end hotels.

We significantly depart from the above studies, especially from Roma et al. (2019), in that we study whether the impact of the sharing economy on incumbents' pricing varies *dynamically*, and how such (possibly) time-varying impact depends on the hotel quality level. The *time factor* has not been examined in any of the papers above, in spite of the relevance of dynamic pricing in the hospitality industry. Dynamic pricing strategies are particularly relevant in this industry, due to its intrinsic characteristics (Blal et al., 2018). In fact, products (e.g., rooms) are intangible and perishable at the same time, subjected to limited and fixed short-term accommodation capacity (Bull, 2006), with high fixed costs, (relatively) low variable costs, as well as no salvage value, if not sold. This implies that, in order to maximize their revenue, hotels need to sell as many rooms as possible within the target day. Due to all these characteristics, including the high demand variability, the adoption of a dynamic pricing strategy is essential in the hospitality industry (Abrate et al., 2012). Hence, understanding how such strategy is influenced by the sharing economy helps provide incumbents with guidelines on how to react to this new phenomenon.

2.2 Theory and hypotheses development

We use two theoretical lenses for our hypotheses development. The first is the economic theory on incumbents' price reactions to new entries. The second is the theory on dynamic pricing for industries where demand is highly uncertain and capacity is fixed in the short term. With regard to the first lens, it is recognized that the entry of new players in the market is likely to affect how incumbents adjust their prices (dynamically) and these reactions depend on the opportunities and threats they expect to face upon the new entry (Caves and Porter, 1977;

Yamawaki, 2002). In particular, lowering prices is a traditional strategy when facing with price-based competition coming from a new entrant (Bresnahan and Reiss, 1991; Thomas, 1999; Simon, 2005). In some cases, this may be obtained cutting on service or product quality (Prince and Simon, 2015). However, other studies have pointed out that incumbents' pricing reactions may vary within the same industry (Frank and Salkever 1997; Yamawaki, 2002), with some firms even raising prices, exhibiting a clear intent to signal differentiation (Prince and Simon, 2015), positioning themselves away from the new entrants especially when the level of competition may get fierce (Gerstner et al., 1993; Kotler and Keller, 2012).

The second lens more directly considers the dynamic nature of pricing in industries with fixed capacity in the short term. The general idea is that in service industries where matching supply and demand is critical given the presence of binding capacity in the short term, prices will be adjusted over time depending on whether excess demand or excess capacity realizes (Gallego and van Ryzin, 1994; Escobari, 2012). In particular, when demand conditions become clearer over time, if excess capacity realizes (and no valuable last-minute demand arises, e.g., business travelers), theory suggests that firms will have strong incentive to reduce the price to dispose such leftover, attracting last-minute price-sensitive consumers (Jerath et al., 2010). On the other hand, if the demand turns out to be high as the service consumption date approaches, firms will tend to raise their prices (Zhao and Zheng, 2000). This literature pinpoints the important role of consumers, distinguishing between those who can plan in advance their purchases (e.g., leisure travelers) and those who learn of their need for the service much later and thus are less price sensitive (e.g., business travelers) (Su, 2007; Jerath et al., 2010; Chen et al., 2014). In particular, the former consumers can behave strategically, meaning that they may choose to anticipate or postpone their purchase according to their own expectations about the pricing trend (Su, 2007; Jerath et al., 2010; Gönsch et al., 2013; Li et al. 2014). Hence, if they believe that prices will be higher (lower) in the future depending the level of demand as compared to the level of supply, they may decide to anticipate (postpone) their purchase, thus intensifying downward pressure on prices early in advance (in later stages) (Shen and Su, 2007; Levin et al., 2009; Chen et al., 2014).

We ground on the theoretical arguments above to formulate and fine-tune our hypotheses to the context of sharing economy. Specifically, as mentioned earlier, by relying on geographically distributed small resources owned by individuals for other scopes, sharing economy platforms are able to provide widely distributed accommodation services at very competitive prices as compared to those offered by traditional players. As a result, sharing economy platforms can be considered as direct competitors (i.e., substitute) for low/medium-end incumbents since they easily attract more price-sensitive leisure consumers by providing them with cheaper offers at comparable service quality (Fang et al., 2016; Hajibaba and Dolnicar, 2017; Griswold, 2016; Zervas et al., 2017; Guttentag et al., 2018; Lim et al., 2021). On the contrary, sharing economy platforms should not exert a substitutive role for high-end providers (e.g., 4-5 star hotels), given that the latter typically offer more sophisticated and higher quality services to valuable consumers, which are willing to pay higher prices. Therefore, even if sharing economy's growth can be considered as a threat for both high-end hotels and low/medium-end hotels, its impact on their reactions in terms of dynamic pricing policy may be different, as they may face different competitive challenges by virtue of the type of consumers targeted (Lee and Jang, 2013; Becerra et al., 2013; Neeser, 2015; Dogru et al., 2017; Zervas et al., 2017; Roma et al., 2019).

Specifically, in line with the classical theory on new entries and prior studies on sharing economy (e.g., Goldsbee and Syverson, 2008; Roma et al., 2019; Sainaghi and Baggio, 2020), low/medium-end hotels, who are likely to face a considerable increase in price-based competition due to the sharing economy entry, should naturally set lower average price (i.e., the average price across of all price offerings of the given hotel for a given accommodation search) in geographical areas (e.g., cities) where sharing economy's penetration is higher, as compared with areas less penetrated by sharing economy. More importantly, we also add that this negative effect of sharing economy on this type of incumbents may vary over time, according to two possible opposite directions.

On the one hand, we advance that hotels facing higher competition from sharing economy players are incentivized to further reduce their prices as the accommodation date approaches, compared to hotels facing lower competition from such players. That is, the negative price gap emerging between low/medium-end hotels in areas characterized by high levels of Airbnb penetration and low/medium-end hotels characterized by mild levels of Airbnb penetration should be amplified as the accommodation date approaches. Indeed, by virtue of the flexible nature of their supply, we could expect the competition coming from sharing economy players to increase when approaching the accommodation date. This is because, as the target date approaches, demand conditions become clearer and, in case of significant demand, hosts who own an underutilized property may decide to make available it for sharing, thus enhancing the overall low/medium-end supply of accommodations (Zervas et al., 2017). In turn, given the high degree of substitutability of sharing economy players and low/medium-end hotels, this would induce fiercer price-based competition when nearing the accommodation date, in order to capture bigger slices from low/medium-end demand, and thus assure the disposal of (excess) capacity (Gallego and van Ryzin, 1994; Escobari, 2012). As a result, based on these considerations the above negative price gap should increase over time.

On the other hand, we also advance that the impact of sharing economy players on incumbents' pricing decisions *over time* may result in an opposite dynamic price trajectory, i.e., in a diminished price gap. Indeed, according to the above arguments on dynamic pricing, in the context of hotel room booking, consumers normally expect that prices of hotel accommodations will be cheaper if they make reservations in advance (Escobari, 2012). For instance, they may save up to 50% if they book the room fortnight in advance before the target day (Guo et al., 2013). Indeed, although the need of selling the remaining capacity before the target day would push hotels to lower prices when approaching the accommodation date, the possibility of taking advantage of the high-end last-minute consumers (e.g., business travelers) should entail higher hotels' average prices near the target date (Zhao and Zheng, 2000; Su, 2007; Guo et al., 2013; Chen et al., 2014). As such, by anticipating increasing prices as the target date approaches, price-conscious consumers targeted by low/medium-end hotels would be more likely to search for an accommodation long before the accommodation date. This strategic behavior becomes even stronger when the level of competition in the market increases (Levin et al., 2009), and hence, in our case, in geographical areas characterized by stronger penetration of sharing economy players. As a result, the price-based competition between low/medium-end incumbents and sharing economy players to attract demand from price-sensitive consumers should be stronger earlier in advance rather than when the accommodation date is close. Accordingly, based on the characteristics of consumers usually targeted by both low/medium-end hotels and sharing economy players, we should observe a more marked price gap earlier in advance. Hence, the negative effect of sharing economy penetration on incumbents' prices should be attenuated *over time*.

As both time-related effects illustrated above may arguably emerge in our setting of study, and the overall effect possibly depends on which one is stronger, we formulate two opposite hypotheses:

H1a: The average prices set by low/medium-end incumbents (i.e., 1-3 star hotels) are lower in geographical areas (i.e., cities) where the level of penetration of sharing economy players *(i.e., Airbnb) is higher, ceteris paribus. Importantly, this negative effect of the level of penetration of the sharing economy increases when the difference between booking and check-in time shrinks.*

H1b: The average prices set by low/medium-end incumbents (i.e., 1-3 star hotels) are lower in geographical areas (i.e., cities) where the level of penetration of sharing economy players (i.e., Airbnb) is higher, ceteris paribus. Importantly, this negative effect of the level of penetration of the sharing economy diminishes when the difference between booking and check-in time shrinks.

As opposite to their low/medium-end counterparts, in general high-end incumbents face a lower competition coming from sharing economy platforms (Zervas et al., 2017; Roma et al., 2019; Sainaghi and Baggio, 2020). Indeed, as mentioned before, high-end hotels typically serve high-end consumers and, only occasionally they target more price-conscious consumers by offering them their services at lower prices (for instance, when they need to dispose their possible excess capacity). As highlighted above, because of the peculiar characteristics of sharing economy players, the entry of these players in a given market would lead incumbents to fierce price-based competition, which would be ultimately non-profitable for high-end hotels (Roma et al., 2019). Indeed, despite the fact that offering lower-prices deals for capturing low/medium-end consumers may be a profitable strategy in some cases (i.e., when there is low demand from high-end consumers) for high-end hotels, prior literature suggests that the excessive price reduction required to successfully compete against sharing economy players would be perceived as inconsistent with their higher service quality by their core target (i.e., high-end consumers), thus reducing profitability (Roma et al., 2019). That is why high-end hotels should concentrate more on their core segment instead of competing with sharing economy players when the threat from these players is significant. As such, they should signal a clear differentiation strategy aiming at positioning far away from the new entrants by reducing discounts and best deals opportunities (Gerstner et al., 1993) and increasing prices when the penetration of sharing economy platforms is stronger (Becerra et al., 2013; Roma et al., 2019).

Importantly, we add that, as this is a strategic positioning decision, it should be consistent over time (Kotler and Keller, 2012). That is, differently from low/medium-end incumbents, in this case, the positive price gap emerging between high-end hotels in areas characterized by high levels of Airbnb penetration and high-end hotels characterized by mild levels of Airbnb penetration should not vary significantly as the accommodation date approaches. It is important to point out that this does not mean that there should not be price changes over time for this type of incumbents. Rather, it suggests that the difference in the price variation over time between hotels subjected to different levels of sharing economy penetration should be largely constant, in light of the price-quality positioning consistency argument. In addition, it should also be highlighted that high-end incumbents are not particularly affected by sharing economy platforms for high-end consumers, given that in general they differ in terms of targeted segments (Zervas et al., 2017; Roma et al., 2019). As such, we should not observe a reduced (i.e., less positive) price gap when the demand from these consumers is more likely to arise, i.e., closer to the accommodation date (Guo et al., 2013; Chen et al., 2014).

Accordingly, we formulate the following hypothesis, which suggests a different pricing effect of the sharing economy on incumbents over time (in particular a stable one), as compared to low/medium-end incumbents:

H2: The average prices set by high-end incumbents (i.e., 4-5 star hotels) are higher in geographical areas (i.e., cities) where the level of penetration of sharing economy players (i.e., Airbnb) is higher, ceteris paribus. Importantly, this positive effect of the level of penetration of the sharing economy does not vary with the difference between booking and check-in time.

3. Data and Methods

3.1 Data

In order to understand how sharing economy influences hotels' dynamic pricing depending on the type of hotel (i.e., the star category), we considered a scenario where a couple of travelers plans a trip in Italy, during the first weekend of June 2018 (June 1st-June 3rd), which is at the beginning of the high season in Italy, and then, looks for a two-night accommodation by considering hotel offerings displayed on Booking.com, the major hotel website in Italy (SiteMinder, 2018). We simulated a scenario where the travelers check the offerings to book their hotel room in different dates in advance: three months before (on March 2nd, 2018), two months before (on April 2nd, 2018), one month before (on May 2nd, 2018), 15 days before (on May 17th, 2018) and 7 days before (on May 25th, 2018). The destinations considered for the above scenario are the top 13 cities visited in Italy, according to the data provided by ISTAT (the Italian Institute of Statistics, www.istat.it): Bologna, Florence, Genoa, Milan, Naples, Padua, Palermo, Pisa, Ravenna, Rome, Turin, Venice, and Verona. These cities display the highest number of registered presences (in terms of booked nights) in Italian traditional accommodation facilities (specifically, all those professional providers not enabled by the sharing economy). We are mostly interested in a spatial comparison (i.e., between different geographical areas/cities) of the effect of sharing economy on incumbent's *dynamic pricing*, rather than in peak vs. valley season comparison. Accordingly, our dataset refers to bookings in a peak season in order to focus solely on our research scope without introducing any other different factor. Specifically, the choice of considering on peak season, instead of valley season, is due to the fact that most of the transactions in the hospitality industry take place during that period, and therefore it can be considered as the most relevant from a business point of view. In fact, dynamic pricing decisions become significantly critical during peak season.

Moreover, we considered only weekend accommodation rather than also considering weekday accommodation because the sharing economy (e.g., Airbnb) has emerged as a competitive alternative of traditional hospitality providers mainly for individuals who travel for leisure purposes and tend to be more price sensitive (Li and Srinivasan, 2019; Roma et al., 2019). For instance, it has been observed that even 90% of Airbnb sales come from leisure travelers (Li and Srinivasan, 2019). Therefore, the choice of considering weekend accommodations, for which most of the bookings are naturally related to leisure purposes, definitely captures the setting where Airbnb can be a dangerous competitor for incumbents. In contrast, weekdays trips include a multitude of bookings also for business purposes, for which the sharing economy is hardly a competitive alternative, especially because business travelers have specific requirements and constraints (time, location, etc.) and in many cases do not directly pay for the service (Li and Srinivasan, 2019). Therefore, we focus on weekend accommodation to better understand the effects of the sharing economy on incumbents' dynamic pricing decisions, given that this is clearly the setting where sharing economy can be a fierce competitor.

To collect the data, we created a crawler simulating the behavior of the couple of travelers on Booking.com. We chose the simplest search on this website where destination (in turn one of the 13 selected cities), check-in date (June 1st), checkout date (June 3rd), number of cameras (1), and number of adults (2) were the only requested information. As our focus is on hotels, we restricted the search to such professional accommodation facilities, implying that other facilities listed on Booking.com such as apartments or bed & breakfast, were excluded from the search. We repeated this simulation for each of our five booking dates. We automatically retrieved all offerings and their characteristics displayed to consumers on Booking.com after each search. Note that, obviously there were often more than one offering coming from the same hotel in the same day of search. This resulted in slightly more than 150,000 price observations collected overall. However, as the analysis is at the hotel level (across the booking dates), we then calculated the average price across the offerings of the same hotel in the given booking date. Afterwards, as it is necessary to include hotel star and the average vote provided by customers to hotels on Booking.com as independent variables in our regression models to control for quality and satisfaction levels, we removed the few hotels that did not display any star category as well as those that did not display any vote from consumers on Booking.com. Therefore, our final sample includes five subsamples of hotel observations (starting from the first accommodation search, on March 2nd, to the last one, on May 23rd) for a total of 13,506 (hotel-day) observations, which correspond to 3,047 hotels and yield an unbalanced panel dataset. In this respect, due to the different scope, our dataset is much larger and cover more booking dates than those used in prior related research (e.g., Roma et al., 2019).

3.2 Variables

Dependent Variable

As our study focuses on the effect of sharing economy on incumbents' dynamic pricing decisions at the hotel level, the dependent variable in our regression models is the average price set by a given hotel in our sample on a given day (across the five search dates before the accommodation date identified above), and computed, as already explained, using the price offerings displayed on Booking.com.

Independent Variables

In order to capture the level of the competition generated by the presence of Airbnb and how this competition may vary over time we introduce two independent variables of our interest. Our first independent variable is the penetration of Airbnb in the given city on the specific period we considered (the first weekend of June 2018), and measured at the accommodation search dates on Booking.com (*City Airbnb Penetration*). Following Roma et al. (2019), we compute this variable as the ratio between the estimated demand of Airbnb and the estimated demand in hotels and similar traditional firms in the given city for the considered period at the different accommodation search dates. This variable really captures how much Airbnb has grown in a given geographical area. Similarly to other studies focusing on Airbnb and pricing strategy (e.g., Gibbs et al., 2017; Oskam et al., 2018), we retrieved data on the demand of Airbnb from AirDNA database. Specifically, we calculated the estimated number of booked nights (related to two-nights periods, as considered in our study) in active properties listed on Airbnb, as the product between the Airbnb occupancy rate and the total number of nights available for two-nights period considering the properties available for booking on Airbnb in the given city in the considered period. Instead, we calculated the demand for hotels and other traditional providers as the estimated tourist flow (in terms of booked nights) in traditional accommodation facilities for that specific period in each city (*City Touristic Flow*), as resulting from data from the ISTAT database.

Our second variable of interest is the interaction between the variable *City Airbnb Penetration* and a variable (*Days Before*) indicating the number of days left to the accommodation (i.e., check-in) date calculated from the booking date. This variable allows us to consider how the *time factor* affects the impact of sharing economy on incumbents' price decisions. This variable is also used in the main model in the form of random effect to take into account the direct effect of time on prices. It is also used as a fixed effect in our robustness checks.

Control variables

The first group of control variables we use in our regression models is related to the characteristics of the city. The data were retrieved from the ISTAT database. In particular, similar to Moreno-Izquierdo et al. (2019), we control for the number of inhabitants (*City*

Population), the per-capita income in euros (*City Per-capita Income*) and, as discussed above, the estimated tourist flow (in terms of booked nights) in traditional accommodation facilities for the considered period in each city in our sample (*City Touristic Flow*). The latter, computed by taking advantage of the detailed tourist flow information for specific periods and geographic areas provided by ISTAT, allows us to control for the level of attractiveness of each city in the considered period, which is very likely to affect hotel prices. Moreover, as the offering of hotels available for booking in a certain date affects the hotel prices (Abrate et al., 2012), we introduce a variable (namely, *Number of Available Hotels in the City*) measuring the number of hotels available for booking at the moment of the accommodation search on Booking.com for the given city in each specific accommodation search date.[2] Finally, we control for a dummy variable indicating whether the city is located in a seaside place (*Seaside Place*), since whether the hotel is located in a beach tourist destination or not is likely to exert a different impact on the hotel prices (Moreno-Izquierdo et al., 2019).

The second group of control variables is at the hotel level. To control for quality and satisfaction levels we introduce a number of variables that have been proven to affect customer experience (e.g., Radojevic et al., 2015): the hotel star category (*Star Category*), the average vote provided by customers to hotels on Booking.com (*Hotel Vote on Booking.com*), and a dummy indicating whether the hotel belongs to a hotel chain or is independent (*Chain*). We also control for the number of rooms of each hotel (*Hotel Room Number*), which represents the overall capacity of each hotel. In addition, we take into account the specific differences between hotels in terms of services provided as they tend to influence customer satisfaction (Khozaei et

[2] Although using the number of rooms available for booking in a certain date would have provided a more precise measure for the competition coming from hotels, using the number of available hotels is still a valuable measure given that we are interested in capturing and distinguishing the effect of the competition coming from the other hotels (traditional competitors) from the effect of the competition due to the presence of Airbnb (the sharing economy competitor).

al., 2016; Radojevic et al., 2015; Saleh and Ryan, 1992), by controlling for a number of dummy variables, such as the presence of a spa and wellness center (*Spa & Wellness Center*), the presence of a swimming pool (*Swimming Pool*), the presence of a restaurant (*Restaurant*), the presence of a parking space (*Parking*), and the presence of free Wi-Fi connection (*Free Wi-Fi*).

Descriptive statistics

According to our hypotheses, we examine how the hotels' *dynamic pricing* strategy, as a reaction to a different level of penetration of Airbnb in different cities, changes based on the hotels quality level. Then, we divided the full sample in two different subsamples: one considering only four and five star hotels (i.e., high-end hotels) and the other one encompassing hotels from one to three stars (i.e., low/medium-end hotels). Table 1 reports the descriptive statistics for all the variables respectively for the 1-3 star hotels, the 4-5 star hotels, and the full sample. From the 3,047 hotels in our sample, 1,965 hotels belong to the 1-3 star category while the remaining 1,082 are 4-5 star hotels. In particular, we count only 4,940 (hotel-day) observations for 4-5 star hotels compared to the 8,566 (hotel-day) observations for the 1-3 star hotels. On average the hotels display 52,68 rooms available for booking. However this value is lower for 1-3 star hotels (32.5) and much higher for 4-5 star hotels (87.6). As expected, 4-5 star hotels are more likely to be part of hotel chains compared to their 1-3 star counterparts (about 20.8% versus 4% of the observations, respectively), to offer spa and wellness center (16% versus 2.4%), swimming pool (16.2% versus 5%), restaurant (57.1% versus 19.2%), parking (68.5% versus 57%) and free Wi-Fi connection (99.1% versus 97.7%) services. Moreover, 4-5 star hotels receive better votes from customers, although there is no large difference between them (about 8.4 versus 7.94, respectively). Regarding the average prices set by hotel, as expected, important differences exist between hotels belonging to different star categories. Specifically, the average prices for a two-night period are on average quite higher in 4-5 star hotels than in

1-3 star hotels (604 versus 255 dollars, respectively). Finally, some considerations about our variable of interest, *City Airbnb Penetration*, are noteworthy. The average value of such variable is equal to 19.19%, suggesting that, on average, Airbnb covered almost a fifth of the demand of accommodations in the period of observation. In turn, this provides evidence that, at least in some cities, Airbnb has gained considerable relevance also in Italy.

Before we move to the empirical analysis, we point out that there emerge no dangerous issues of collinearity in our sample from performing correlation matrix and the VIF analyses after our regression models (in the interest of length correlation statistics are omitted and can be made available by the authors).

4. Empirical analysis and results

As our sample consists of panel data, to test our hypotheses we performed a two way random-effects regression model, which takes into account both the effect of each individual hotel and the time effect as we move from the most distant observation from the accommodation date to the closest one.[3] We chose this model rather than fixed-effects model because of some of our control variables at both hotel and city levels, such as *Star category*, *Chain*, *Hotel Room Number*, *Swimming Pool*, *Restaurant*, *Seaside Place*, *City Population* and others, are time-invariant at least in the short term, although they obviously change from one hotel to another. At any rate, in Section 5, we show full robustness of our findings under different model specifications, including the fixed effects model. As mentioned in the previous section, in line

[3] Considering a random coefficient model could also be a valid approach. However, it has the problem of making difficult to discern how the moderator (i.e., the difference between booking time and check-in time) influences the effect of Airbnb penetration on hotels' dynamic pricing. This is because, by treating the variation over time as a random component, the random coefficient model provides only standard deviation of the base coefficient (i.e., *City Airbnb Penetration*), without providing any direct indication of whether the relationship is magnified or reduced over time. On the contrary, our approach of using two-way random effects model and capturing the effect of *City Airbnb Penetration* on incumbents' dynamic pricing through its interaction with the variable *Days Before* easily allows to see how such relationship changes as the check-in date is approached.

with our hypotheses, we analyzed the two subsamples of 1-3 star hotels and 4-5 star hotels, separately. In the first two columns of Table 2 we report the results without and with the interaction term respectively under the subsample of only 1-3 star hotels, whereas in the second two columns we report those related to the subsample of only 4-5 star hotels.[4]

For the 1-3 star hotels subsample, the results related to hotel-level characteristics mostly confirm our expectations. While star category and customers' vote on Booking.com positively and significantly influence hotel prices, the effect of the services offered by the hotel tends to be mostly significant and negative for the presence of restaurant and parking space. The latter can be explained by considering that 1-3 star hotels generally do not include these services in their basic offering, but they offer them only upon additional payments under the add-on pricing logic (Geng et al., 2018). Conversely, the effect of the presence of a swimming pool is instead insignificant, whereas the presence of free Wi-Fi and spa and wellness center is positive and significant. With regard to the presence of a spa and a wellness center, the few low-medium end hotels (specifically 3-star hotels) who are able to offer such specific high-end service probably use it as an element of differentiation from hotels within the same star category, thus raising the hotel prices. With regard to the presence of free-Wi-Fi, its free fruition naturally tends to raise the price in low/medium-end hotels. Hotel prices are also not affected by belonging to a chain rather than being an independent hotel. This can be explained by the fact that a potential "economies of scale" effect is already accounted for by the presence of number of hotel rooms, which has indeed a negative and significant impact on prices. Regarding variables at the city level, ceteris paribus, the average prices of 1-3 star hotels tend to be higher in cities located in a seaside area, having lower population with a lower per-capita income, attracting a higher

[4] A good way to compare the goodness of the (two-way) random effect model is to run a likelihood ratio test, which is shown to be largely significant at the bottom of Table 2.

number of tourists and having lower number of hotels available for booking at the date of the accommodation search. The latter effect is particularly important as it suggests that, as expected, hotels set lower prices when the number of hotels available for booking increases, i.e., when the degree of competition among hotels is higher.

Moving to our first hypothesis, we have argued that, *ceteris paribus*, 1-3 star hotels tend to set lower prices when they are located in cities where the competition from Airbnb is higher, rather than when they are located in cities less penetrated by Airbnb. More importantly, we have also advanced that this negative price gap can either increases or decrease as the accommodation date approaches. To our scopes, we first test the average effect of the variable *City Airbnb Penetration* by introducing this variable only in its level form (first column of Table 2) and then we also add its interaction with the variable *Days Before* (i.e., the number of days left before approaching the accommodation date) to capture any possible time-related effect of the level of sharing economy penetration (second column of Table 2). Note that we subtract a value of seven from the variable *Days Before*, so that, in the model with the interaction, the effect of the variable *City Airbnb Penetration* in its level form captures the effect of the sharing economy penetration seven days before reaching the accommodation date (i.e., in our last day of observation).

The results in the first column of Table 2 show that the average effect *City Airbnb Penetration* on the average prices set by 1-3 star hotels is not significant as the coefficient of this variable is largely not significant. However, the results in the second column of Table 2 document that, while the variable *City Airbnb Penetration* is still not significant, its interaction with the variable *Days Before* has a significant and negative impact on the average prices set by 1-3 star hotels. This implies that the negative effect of sharing economy on low/medium-end hotels actually arises when booking quite early in advance and it tends to vanish approaching the accommodation date. In other words, the negative price gap emerging between low/medium-end hotels in areas characterized by high levels of Airbnb penetration and high/medium-end hotels characterized by mild levels of Airbnb penetration exists when being far from the accommodation date and gradually disappears when nearing the accommodation date. This provides support to our hypothesis *H1b* against *H1a* and nurtures our arguments on the time-varying effect of the sharing economy in the dynamic pricing decisions of low/medium-end incumbents. That is, for low/medium-end hotels, the level of sharing economy penetration does affect incumbents' dynamic pricing decisions, as it is shown to be more marked when booking early in advance. As explained, consumers usually attracted by low/medium-end incumbents as well as by sharing economy players are price-conscious and tend to book early in advance to avoid any price increase over time. As a result, competition between these players for capturing this demand mostly occurs in the early period rather than close to the accommodation date, even though the flexible nature of the sharing economy may suggest the opposite. Indeed, consistent with the logic that the sharing economy induces competitive prices, the majority of sharing economy suppliers (i.e., Airbnb hosts) mostly compete for price-sensitive consumers, who typically book their services early in advance. In contrast, close to the service consumption date, only sharing economy providers characterized by high reservation utility (who are typically a minority of Airbnb hosts) supply their resources, thus naturally diminishing the competitive pressure on prices in this case. As a result, consistent with *H1b*, the negative effect of the sharing economy penetration on low/medium-end incumbents tend to be higher early in advance.

In the second two columns of Table 2, we report the same analyses under the sample of only 4-5 star hotels. The effect of control variables is mostly similar as before, although there exist some exceptions. Similarly to 1-3 star hotels, also for 4-5 star hotels, star category, customers' vote on Booking.com, the presence of a spa and wellness center and the city touristic flow exert a positive and significant effect on hotels' average prices, whereas city population, city per-capita income, the number of hotels available for booking in the given city at the moment of reservation, and the presence of parking space negatively and significantly influence average prices, with the role of hotel ownership being mostly insignificant. Unlike 1-3 star hotels, being located in a seaside area, offering a restaurant service as well as the hotel room number exert no significant impact on prices for 4-5 star hotels, whereas the effect of services such as swimming pool and Free Wi-Fi is instead surprisingly negative and significant.

More importantly, regarding our variables of interest in the case of high-end hotels, the coefficient of the variable *City Airbnb Penetration* is positive and significant when introduced without interaction in the third column of Table 2, confirming the finding in prior literature than high-end hotels tend to set higher prices in geographical areas characterized by higher sharing economy penetration (Roma et al., 2019). More interestingly, when adding its interaction with the variable *Days Before*, the variable *City Airbnb Penetration* remains positive and significant in its level form, but the interaction terms is largely insignificant. This implies that there is no change in the effect of the variable *City Airbnb Penetration* as the accommodation date approaches. It remains positive and of the same magnitude, thus confirming our hypothesis *H2*. As explained, the strategy of high-end incumbents of differentiating away from lower-end firms and focusing more on their core segment by raising prices in geographical areas where the sharing economy is a more insidious threat needs to be consistent over time to be effective, as standard marketing literature suggests (Kotler and Keller, 2012). As a result, differently from low/medium-end incumbents, in this case the positive price gap emerging between high-end hotels in areas displaying high levels of Airbnb penetration and high-end hotels in areas characterized by mild levels of Airbnb penetration emerges and does not vary significantly as the accommodation date approaches.

5. Robustness checks

In this section we show robustness of our findings by using different regression models. In particular, in the previous section we have used a two-way random effects model to take into account, as random effects, both the effect of each individual hotels and the time effect as we move from the booking date to the check-in date. However, we test two other suitable regression model options for our analysis. We consider single random effect, capturing only the effect of each individual hotel as a random effect, while controlling for the time effect as a fixed effect through the variable *Days Before*. The remaining variables are the same as those utilized in the main model. Table 3 reports the results for 1-3 stars and 4-5 stars hotels, respectively. As it can be noticed, our findings are fully confirmed. Moreover, the large significance of the Breusch-Pagan test shows that this model is preferable to the standard pooled OLS.

The second model option is to use the fixed effect model where we capture the effects of individual hotels and time as fixed effects (the effect of time using the variable *Days Before*). As pointed out earlier, we did not choose the fixed effects model as the main model because all time-invariant control variables would be dropped from the model as they are captured by the fixed effect, preventing us from understanding their influence on the price levels over time. Luckily, our variable of interest *City Airbnb Penetration* and its interaction with the variable *Days Before* are among the few variables being time-varying. This allows us to actually run the fixed effects regression model. Specifically, Table 4 shows that our findings are fully robust also under the fixed effects model. That is, hypotheses *H1b* and *H2* are once again supported. At the bottom of the Table 4 we report the Hausman test that compares the fixed effects model with the (one-way) random effects model, showing a clear preference for the former. Nevertheless, since our results are fully robust across the models and given that we want to avoid dropping numerous important time-invariant control variables, we decided to maintain the two-way random effects model as the main model and report the fixed effects model as a robustness check.

6. Discussion and conclusion

Our study complements prior contributions on the effect of the sharing economy on incumbents' pricing decisions by exploring the role of the *time factor* in a dynamic pricing context. Specifically, we shed light on whether the sharing economy penetration affects the way incumbents adjust their pricing decisions dynamically in the hospitality industry. To address our research question, we have built an *ad-hoc* sample of panel data consisting of more than 150,000 hotel price offerings from more than 3,000 hotels located in the 13 top visited cities in Italy.

Our study demonstrates that sharing economy players' penetration influences incumbents' *dynamic pricing* policy, differently depending on incumbents' quality level (high-end versus low/medium-end hotels). Specifically, our finding suggests that prices of low/medium-end incumbents are lower in geographical areas where sharing economy penetration is higher, rather than where it is milder, thus confirming that peer-to-peer platforms are effective substitute for low/medium-end hotels. However, this negative price gap actually occurs when booking quite far from the accommodation date and tends to disappear when the accommodation date gets close, according to the price-conscious consumers' tendency of advance booking. On the contrary, high-end hotels react to Airbnb's entry by setting higher prices in geographical areas where Airbnb's penetration is higher, in order to escape any price competition against this insidious new entrant and concentrate more on their target segment (i.e., high-end consumers). Interestingly, such tendency is maintained constant over time, due to the need of preserving the consistence of the price-quality positioning.

Our study has some important implications for the extant literature. First of all, we contribute to the knowledge on pricing by examining how incumbents' pricing decisions vary or do not vary when facing new disruptive entrants, such as sharing economy players. In particular, we considerably add to the stream of literature on price reactions to new entries as well as to that on dynamic pricing (Bresnahan and Reiss, 1991; Thomas, 1999; Simon, 2005; Su, 2007; Jerath et al., 2010; Abrate et al., 2012; Gönsch et al., 2013; Li et al. 2014; Shen and Su, 2007; Zhao and Zheng, 2000), by demonstrating that incumbents' pricing decisions depend on the level of penetration of unconventional and disruptive new entrants, such as sharing economy players, in a nontrivial manner. In fact, we find that these decisions may or may not change as the service consumption date gets closer depending on the type of service quality offered (e.g., high vs. medium-low class). In this respect, we also advance knowledge on the pricing implications of sharing economy. In particular, we add to prior literature on the consequences of sharing economy (e.g., Zervas et al., 2017; Heo et al., 2019; Roma et al., 2019; Sainaghi and Baggio, 2020; Yang and Zhenxing, 2020) by clarifying that the negative price effect of sharing economy on low/medium-end incumbents does not always emerge. Rather, it occurs when the demand from price-sensitive consumers is more likely to be manifest, i.e., well in advance compared to the service consumption date. Vice versa, the positive price effect of sharing economy on high-end incumbents does emerge irrespective of the difference between booking and consumption times.

Our study has practical implications for incumbents in the hospitality industry facing competition from new sharing economy platforms such as Airbnb. The direct implication of our conclusions is that incumbents in the hospitality industry should pay significant attention on the sharing economy' penetration level in the area where they operate as the sharing economy can have a non-negligible impact on their pricing decisions depending on the type of incumbents (low/medium-end vs. high-end) and on the temporal distance from the service consumption date.

In particular, low/medium-end incumbents should be aware that the threats from the sharing economy will be higher in early advance periods. That is, the price competition entailed by the sharing economy will most likely be manifest when booking early in advance due to the strategic behavior of leisure travelers who typically tend to anticipate their purchases, as well as the flexible nature of the sharing economy. As such, in terms of dynamic pricing and revenue management, low/medium-end incumbents could consider offering quite attractive deals (in terms of price) early in advance to better compete with the disruptive new entrant. On the other hand, they should not be worried much when booking occurs close to the service consumption date. Consequently, they may consider fine-tuning their strategy based on the temporal distance from service consumption date, putting greater emphasis on competitive prices for offerings far from the accommodation date, while emphasizing service features when close to such date.

High-end incumbents should instead ensure price-quality consistency over time if they pursue a differentiation strategy by increasing their prices in areas where sharing economy is a more relevant threat. In this case, differently from low/medium-end hotels, the dynamic pricing strategy of high-end hotels would not be affected considerably by the presence of the sharing economy.

Finally, our study has also some implications for consumers, and consequently for policy makers. Indeed, our study enhances price-conscious consumers' awareness about whether and how low/medium-end and high-end hotels' prices will vary over time depending on the penetration of the sharing economy. In turn, this informs them on the most favorable timing to book their accommodations depending on the penetration of sharing economy players in the area where they seek accommodation. Consumers of low/medium-end hotels may find more convenient early in advance as in this case competition is likely to be intense and prices will drop. Vice versa, consumers of high-end hotels should not be worried much about the effect of sharing economy penetration since it does not affect the price trajectories over time.

Our findings and implications do not take into account the tremendous impact the COVID-19 pandemic is having on the tourism industry. However, while leaving the comparison of incumbent's dynamic pricing reactions to sharing economy penetration in normal versus abnormal (e.g., pandemic) times for future research, we endeavor to conjecture how COVID-19 may influence the relationships studied in this paper. It is expected that travelers will pay much more attention on safety and health issues when making travel-related purchase decisions (Proserpio, 2020), which could push them back to favor services offered by hotels rather Airbnb accommodation. Moreover, the conjectured negative effect of COVID-19 on the sharing economy will be likely based not only on the demand side, i.e., the preferences of guests, but also on the fact that the host propensity to share their houses/apartments with strangers will be likely lowered due to the same health concerns, especially in case of the more susceptible aging hosts. As a result, we conjecture that the potentially lowered strength of the sharing economy may result on reduced impact on the relationships identified in this paper for dynamic pricing decisions. This is not because the dynamics identified in this paper will no longer be valid – they will still hold even in the post-COVID-19 era – but simply because the effects will be attenuated by changes in the consumer behavior related to COVID-19.

This potentially lowered effect may not apply post the pandemic especially in the long term if sharing economy players will be able to re-organize their businesses in a way that these health and safety concerns will be overcome. It is indeed undoubted that the economic crisis due to the COVID-19 pandemic has become a stress test for sharing economy players, including Airbnb, forcing them to experiment with different solutions to enable re-conversion of underutilized resources and maintain their business model sustainable (Proserpio, 2020). Nevertheless, by taking advantage of the intrinsic flexibility and scalability of their business models, these companies have been able to survive the pandemic, in spite of the fact they were among the companies most hit by the pandemic, and they are now recovering at a good pace (Yohn, 2020). For instance, following COVID-19, Airbnb has refocused on its original core business, i.e., peer-to-peer budget home rental, by targeting travelers who wanted to stay away from larger hotels and remote workers looking for long-term rentals. At the same time, Airbnb has significantly streamlined ancillary services that were gradually added before the pandemic, such as traditional hotel and luxury property listings (Yohn, 2020). As a result, also from a financial point of view, industry experts are suggesting that the value of these companies may soon come back to the pre-COVID period (Gallagher, 2020). These arguments are supported by Airbnb's positive financial performance at the end of 2020 and at the beginning of 2021 (Yohn, 2000; Airbnb, 2021). This indicates that the sharing economy are positively (though slowly) countering the recent crisis and that this business is likely to fully recover once the pandemic will be over. Therefore, the implications of our results, derived under a normal period, will probably be still relevant in the future as sharing economy will not disappear, but rather will be a relevant component of the hospitality industry in the new normal.

In addition to the study of the impact of COVID-19, future studies could address our research questions in another industry where the sharing economy has become prominent, i.e., the car transportation service industry. Future improvements could also extend to other geographical markets (e.g., other countries) and/or explore whether the results obtained in our study depends on the period of the year (i.e., peak vs. valley season). We conjecture that considering also valley season would not significantly change our findings since the level of competition, as well as the presence of Airbnb, would not change significantly and, even if it were to be the case, it would pertain to periods, which are characterized by a smaller number of transactions (and consequently by a smaller relevance for the industry). Similarly, although we have pointed out that the sharing economy tend to be a strong competitor mostly for leisure travelers, future research could still consider how its impact changes between weekend and weekday types of accommodation, gathering data after the COVID-19 pandemic (and its effects) will be over.

Moreover, while our paper focuses on how different sharing economy penetration across different geographical areas influences dynamic pricing of hotels, another important research question left for future research would be the investigation of pricing dynamics characterizing Airbnb hosts. Future studies could indeed examine how several factors such as host ratings, host behavior (e.g., responses to guest, service level), host-guest interactions, platforms' decisions and rules, etc., affect Airbnb hosts' pricing decisions. Finally, future studies could examine how the growth of sharing economy players and the consequent incumbents' reactions (such as those identified in the present study) may influence the profitability of both types of players as well as the consumer welfare over time.

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Table 1. Descriptive statistics by hotel star category

Variables	1-3 Star Hotels (8,565 observations) Mean	Std. Dev.	4-5 Star Hotels (4,939 observations) Mean	Std. Dev.	Full Sample (13,504 observations) Mean	Std. Dev.
Average Hotel Price (Dollars)	255.287	127.912	604.645	646.748	383.062	437.786
Star Category	2.587	0.667	4.128	0.334	3.151	0.934
Hotel Vote on Booking.com	7.944	0.746	8.402	0.602	8.112	0.731
Chain	0.040	0.196	0.208	0.406	0.101	0.301
Hotel Room Number	32.509	33.491	87.664	76.951	52.682	59.855
Swimming Pool	0.050	0.219	0.162	0.368	0.091	0.288
SPA & Wellness Center	0.024	0.154	0.161	0.368	0.074	0.262
Restaurant	0.192	0.394	0.571	0.495	0.331	0.470
Parking	0.570	0.495	0.685	0.464	0.612	0.487
Free Wi-Fi	0.977	0.150	0.991	0.095	0.982	0.133
City Touristic Flow	70,751.25	56,796.03	77,779.83	55,615.79	73,321.9	56466,74
City Per-capita Income (Euros)	18.152	2.826	18.376	3.259	18.234	2.993
City Population	1,216,014	1,110,827	1,350,259	1,096,322	1265113	1107393
Seaside Place	0.577	0.494	0.565	0.496	0.572	0.495
Number of Available Hotels in the City	408.114	292.088	434.025	294.168	417.590	293.106
City Airbnb Penetration	0.183	0.113	0.206	0.117	0.192	0.115

Table 2. Two-way random-effects regression models

	1-3 Star Hotels (without interaction)	1-3 Star Hotels (with interaction)	4-5 Star Hotels (without interaction)	4-5 Star Hotels (with interaction)
Star Category	0.220*** (0.010)	0.220*** (0.010)	0.959*** (0.037)	0.959*** (0.037)
Hotel Vote on Booking.com	0.147*** (0.008)	0.148*** (0.008)	0.335*** (0.018)	0.335*** (0.018)
Chain	-0.008 (0.034)	-0.008 (0.034)	-0.032 (0.029)	-0.032 (0.029)
Hotel Room Number	-0.0004** (0.0002)	-0.0004** (0.0002)	0.000 (0.000)	0.000 (0.000)
Swimming Pool	-0.020 (0.032)	-0.021 (0.032)	-0.075** (0.035)	-0.075** (0.035)
SPA & Wellness Center	0.187*** (0.040)	0.185*** (0.040)	0.130*** (0.034)	0.130*** (0.034)
Restaurant	-0.054*** (0.019)	-0.055*** (0.019)	0.030 (0.027)	0.030 (0.027)
Parking	-0.089*** (0.015)	-0.090*** (0.015)	-0.098*** (0.028)	-0.098*** (0.027)
Free Wi-Fi	0.091** (0.045)	0.091** (0.045)	-0.325*** (0.118)	-0.325*** (0.118)
City Touristic Flow	0.385*** (0.015)	0.381*** (0.015)	0.443*** (0.028)	0.443*** (0.028)
City Per-capita Income (Euros)	-0.241*** (0.057)	-0.245*** (0.057)	-0.619*** (0.100)	-0.619*** (0.100)
City Population	-0.193*** (0.010)	-0.193*** (0.010)	-0.217*** (0.019)	-0.217*** (0.019)
Seaside Place	0.067*** (0.021)	0.064*** (0.021)	0.005 (0.040)	0.005 (0.040)
Number of Available Hotels in the City	-0.0003*** (0.000)	-0.0003*** (0.000)	-0.0003*** (0.000)	-0.0003*** (0.000)
City Airbnb Penetration	-0.010 (0.024)	-0.010 (0.025)	0.101*** (0.032)	0.100*** (0.035)
City Airbnb Penetration X Days Before	-	-0.001** (0.000)	-	0.000 (0.001)
Constant	2.936*** (0.220)	2.986*** (0.222)	-0.226 (0.412)	-0.226 (0.412)
ID_Hotel (random hotel effects - std. dev. intercept)	0.280 (0.005)	0.280 (0.005)	0.362 (0.008)	0.362 (0.008)
Days Before (random time effects - std. dev. intercept)	0.096 (0.001)	0.096 (0.154)	0.106 (0.226)	0.106 (0.002)
N. obs	8566	8566	4940	4940
N. hotels	1965	1965	1082	1082
LR Chi^2 (p-value)	10440.6 (0.000)	10445.3 (0.000)	7016.8 (0.000)	7015.5 (0.000)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Random effects parameters (ID_Hotel and Days Before) significant at 5% level or better (1%).

Table 3. One-way random-effects regression models

	1-3 Star Hotels (without interaction)	1-3 Star Hotels (with interaction)	4-5 Star Hotels (without interaction)	4-5 Star Hotels (with interaction)
Star Category	0.220*** (0.010)	0.220*** (0.010)	0.959*** (0.037)	0.959*** (0.037)
Hotel Vote on Booking.com	0.147*** (0.008)	0.147*** (0.008)	0.335*** (0.018)	0.335*** (0.018)
Chain	-0.008 (0.034)	-0.009 (0.034)	-0.032 (0.029)	-0.032 (0.029)
Hotel Room Number	-0.0004** (0.0002)	-0.0004** (0.0002)	0.000 (0.000)	0.000 (0.0000)
Swimming Pool	-0.020 (0.032)	-0.021 (0.032)	-0.075** (0.035)	-0.075** (0.035)
SPA & Wellness Center	0.187*** (0.040)	0.185*** (0.040)	0.130*** (0.034)	0.130*** (0.034)
Restaurant	-0.054*** (0.019)	-0.056*** (0.019)	0.030 (0.027)	0.031 (0.027)
Parking	-0.089*** (0.015)	-0.090*** (0.015)	-0.098*** (0.028)	-0.098*** (0.028)
Free Wi-Fi	0.091** (0.045)	0.090** (0.044)	-0.325*** (0.118)	-0.325*** (0.118)
City Touristic Flow	0.384*** (0.015)	0.381*** (0.015)	0.443*** (0.028)	0.443*** (0.028)
City Per-capita Income (Euros)	-0.235*** (0.057)	-0.257*** (0.058)	-0.617*** (0.100)	-0.613*** (0.101)
City Population	-0.195*** (0.010)	-0.189*** (0.011)	-0.217*** (0.019)	-0.219*** (0.020)
Seaside Place	0.068*** (0.020)	0.061*** (0.021)	0.005 (0.040)	0.006 (0.040)
Number of Available Hotels in the City	-0.0003*** (0.000)	-0.0003*** (0.000)	-0.0003*** (0.000)	-0.0003*** (0.000)
Days Before	0.0001 (0.0001)	-0.0001 (0.0001)	0.000 (0.0001)	0.000 (0.0001)
City Airbnb Penetration	-0.009 (0.033)	-0.014 (0.034)	0.108** (0.052)	0.113*** (0.056)
City Airbnb Penetration X Days Before	-	-0.001** (0.0006)	-	0.0002 (0.0008)
Constant	2.948*** (0.221)	2.968*** (0.220)	-0.229 (0.412)	-0.225 (0.412)
N. obs	8566	8566	4940	4940
N. hotels	1965	1965	1082	1082
rho	0.862	0.861	0.894	0.895
Breusch-Pagan test Chi^2 (p-value)	11439.0 (0.000)	11433.1 (0.000)	7239.8 (0.000)	7263.1 (0.000)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Fixed-effects regression models

	1-3 Star Hotels (without interaction)	1-3 Star Hotels (with interaction)	4-5 Star Hotels (without interaction)	4-5 Star Hotels (with interaction)
Hotel Vote on Booking.com	-0.019 (0.023)	-0.019 (0.023)	0.003 (0.045)	0.003 (0.045)
Number of Available Hotels in the City	0.0001 (0.0001)	0.0001 (0.0001)	0.0002 (0.0002)	0.0002 (0.0002)
Days Before	0.0002** (0.0001)	-0.0001 (0.0001)	0.002 (0.002)	0.002 (0.002)
City Airbnb Penetration	0.037 (0.035)	-0.003 (0.037)	0.121** (0.048)	0.121** (0.048)
City Airbnb Penetration X Days Before	-	-0.002*** (0.0006)	-	0.0001 (0.0006)
Constant	5.548*** (0.186)	5.543*** (0.186)	5.967*** (0.391)	5.968*** (0.391)
N. obs	8566	8566	4940	4940
N. hotels	1965	1965	1082	1082
rho	0.936	0.936	0.966	0.966
F test (p-value)	48.09 (0.000)	47.63 (0.000)	85.620 (0.000)	85.390 (0.000)
Hausman test (p-value)	127.667 (0.000)	149.328 (0.000)	103.938 (0.000)	120.904 (0.000)

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$