Are mom-and-pop and professional hosts actually competing against hotels?

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ABSTRACT

Design/methodology/approach

The cities of Milan and Rome are used as case studies for this analysis. To assess the extent of synchronization, the series of Airbnb and hotels are transformed into a series of symbols that render their rhythmic behavior, and a mutual information metric is used to measure the effect.

Purpose

The question of whether commercial, peer-to-peer accommodation platforms (Airbnb, in particular) and hotels are in fierce competition with each other with the possible presence of substitution threats is examined in this work, which compares the time series of the occupancy values across two supplier types.

Findings

The results show that Airbnb hosts and hotels have different seasonal patterns. The diverse occupancy trends support the absence of direct competition between Airbnb and hotels. The findings are consistent in the two analyzed cities (Milan and Rome). Interestingly, there are higher similarities between seasonal occupancy series of Airbnb listings in Milan and Rome, on one side, and hotels in Milan and Rome, on the other, than between Airbnb and hotels in the same city.

Research limitations/implications

The findings show a progressive de-synchronization (within mutual information) among the five groups of Airbnb hosts, triggered by the rising professionalization degree. This result suggests the existence of a partial different business model for multi-listing hosts.

Practical implications

The study illustrates an absence of any substitution threat between Airbnb and hotels in both cities. This could have important consequences, especially for the pricing and revenue management policy. In fact, the higher the substitution threat, the higher the attention that Airbnb entrepreneurs should pay to the pricing strategy implemented by hotels, and vice versa.

Originality/value

This study sheds new light on the competition threat between Airbnb and hotels. In this study, hotels and Airbnb hosts appear as two very separate markets.

Keywords

Competition; Professional hosts; Airbnb; Hotel classes; Synchronization; Mutual information

1. INTRODUCTION

Since the development of commercial peer-to-peer accommodation platforms (P2P APs), there has been a boom in academic papers exploring this phenomenon (Tang *et al.*, 2019; Zhu *et al.*, 2019). The rising interest is epitomized in the number of recent literature reviews focused on the so-called sharing economy in the hospitality and tourism industry (Altinay and Taheri, 2019; Dann *et al.*, 2019; Dolnicar, 2019; Prayag and Ozanne, 2018; Sainaghi and Baggio, 2019a; Sainaghi *et al.*, 2019a; Sainaghi *et al.*, 2020a). Within this debate, a key topic was and remains the ability of paid P2P APs (Airbnb *in primis*) to compete against traditional hotels (Prayag *et al.*, 2020). In this paper, a commercial P2P AP is defined as "space suitable for overnight stays sold by a […] provider (the host) to an end user (the guest) for short-term use through direct [or online] interaction between host and guest" (Dolnicar, 2019, p. 248). In the original definition, Dolnicar suggested that a host is a "non-commercial" provider. This expression was removed due to the increasing number of professional hosts, defined as providers, who manage more than one listing (Deboosere *et al.*, 2019; Gunter and Önder, 2018; Wang and Nicolau, 2017).

What is the competition threat to hotels generated by Airbnb listings? Papers have proposed varying answers to this question. An initial group of studies (Aznar *et al.*, 2017; Guttentag, 2015; Heo *et al.*, 2019; Koh and King, 2017) suggested that the substitution threat is limited, mainly because the number of Airbnb listings represents a small niche and attracts a different market segment (mainly leisure) from guests attracted by hotels (Guttentag, 2015). Over the years, the number of Airbnb listings has been dramatically augmented (Chica-Olmo *et al.*, 2020), and, therefore, the niche argument is now more nuanced (Oskam and Boswijk, 2016). Furthermore, a new research stream, the so-called P2P APs spatial patterns, revealed that the listing locational patterns are mainly centrally located and are not far from destination attractions, showing a similar distribution to hotels (Boros *et al.*, 2018; Gutiérrez *et al.*, 2017). According to this new scenario, the substitution threat is expected to be more intense. This is the conclusion stated by Zervas *et al.* (2017). Analyzing many years' worth of data, the authors estimated that a 1% rise in Airbnb listings in Texas resulted in a 0.05% reduction in hotel revenue. Apparently, the substitution threat is very marginal. However, if Airbnb listings rise

by 20–30%, the decrease in hotel sales may not be so marginal. Similarly, Xie and Kwok (2017) identified a potential substitution for hotel demand, as well as a consequent reduction in revenue per available room. The substitution threat is expected to be more relevant for low-end hotels (economy class) than for midscale or luxury hotels (Pizam, 2014; Tussyadiah and Pesonen, 2016). In fact, generally speaking, Airbnb attracts more price-sensitive travelers, which increases its competition with low-end hotels, as confirmed by some studies (Guttentag and Smith, 2017; Hajibaba and Dolnicar, 2017; Zervas *et al.*, 2017).

More recently, some articles have been published about this topic, and their findings are somewhat different. Ginindza and Tichaawa (2019) analyzed the reciprocal effect generated by hotel occupancies on listing occupancies, and vice versa, showing that hotel performance and listing performance increase in tandem. Furthermore, the authors suggested that the two products may be viewed as non-competitors. The study focused on the Kingdom of Swaziland (bordering on South Africa and Mozambique). Another study, based on the agent-based model, revealed a low substitution threat between short-term accommodation markets and traditional hotels (Bruno and Faggini, 2020), considering that guests are differentiated in term of preferences. The study showed the relevance of the demand level, which will play a pivotal role in the next quarters, due to the effects of Covid-19. More recent studies confirmed these polarized results. For example, Dogru *et al.* (2019) found a negative effect generated by Airbnb on traditional hotels in ten major U.S. markets. In contrast, Sainaghi and Baggio (2020) found limited competition between the two lodging segments. In fact, Airbnb hosts focused more on leisure segments, while hotels focused on business and trade-fairs (the author analyzed a business destination). The overlap among Airbnb and hotels was very limited on midweek days, trade-fair days, and workdays (as defined in the cited study), but it rose on weekends and during holidays.

This short analysis illustrates that current studies exploring the substitution threat among Airbnb and hotel have contradictory results. This paper contributes to filling this gap (ranging from absence to high competition between Airbnb listings and hotels) by adopting a different approach. In fact, previous studies were conducted primarily around the measurement of impacts generated by Airbnb listings on hotel results, using performance indices, such as average daily rate, revenue, occupancy rate, or financial ratios (Aznar *et al.*, 2017; Blal *et al.*, 2018; Choi *et al.*, 2015). In this study, attention is given to the degree of synchronization (mutual information) between Airbnb and hotels, which involves comparing their respective time series. The method compares time series and measures the similarities and differences among them. The comparison is based on three steps (later also presented using mathematical language). The higher the degree of synchronization, the higher the substitution threat, and vice versa. Therefore, the central research question of this article focuses on the similarities and differences between the time series of Airbnb listings and hotels. If the two series show different seasonal patterns—for example, hotels reach high occupancy rates and revenues midweek and lower performance on the weekends, and the opposite results are achieved by Airbnb listings—then a lower substitution threat is considered. The opposite conclusion is stated when Airbnb and hotel series show a very similar synchronization degree. In the methodology section, the precise meaning of "synchronization" is given, as well as a description of the quantitative analysis carried out. This paper is rooted in the management research stream, with a focus on competitive threat. As anticipated, the methodology is based on time series. In order to develop a comparative analysis between Airbnb and

hotel performance metrics, the seasonal patterns of the two cities included in the sample are considered.

2. LITERATURE REVIEW

Adopting a prevalent supply-side approach, but not ignoring the demand or market approach (Leiper, 1979), this section investigates the expected degree of similarity, as well as difference, between hotels and listings, based on previous studies, as later presented and discussed. In other words, generally speaking, it seeks to determine whether the Airbnb series are similar to those of hotels. The distinction between the supply side (firms) and the demand side (clients and markets) is very relevant in tourism and hospitality, as epitomized by the famous dialogue between two seminal authors, Leiper (1979) and Smith (1988). While the supply side focuses on organizations (in this paper, hotels and Airbnb hosts), the demand approach focuses on guests and markets. This paper primarily adopts a supply approach, but it does not ignore some demand considerations. Both perspectives (demand and supply) are relevant, but considering the object of this article (substitution threat), supply arguments are more central.

The literature analyzing the determinants of a listing's performance is particularly insightful. The identified price and, more generally, the performance antecedents (Sainaghi *et al.*, 2020b) are usually considerably different when comparing hotels and Airbnb providers (Wang and Nicolau, 2017). These determinants influence the substitution threat among the two lodging segments (Xie *et al.*, 2019). This conclusion depends on some distinctive features (antecedents or determinants) of each lodging segment (Airbnb and hotels), based on the following variables: i) supply attributes, ii) managerial competences, iii) contractual conditions, iv) economic variables, v) motivations, and vi) relationships with guests. These six variables are identified based on the analysis of the supply-side papers, discussed below.

Concerning *attributes*, Airbnb supply is primarily centered around the entire home/apartment category (Chica-Olmo *et al.*, 2020). An apartment and, even more so, a house are completely different from a hotel room. The listing services (usually called amenities) are partially different from hotels, especially in their number (Wang and Nicolau, 2017). For example, in the study by Falk *et al.* (2019), 40 listing attributes were considered, while Chattopadhyay and Mitra (2019) included 143 items. The sizes of Airbnb listings are normally larger than hotel rooms, thus accommodating a larger number of people (Gibbs *et al.*, 2018a, 2018b). Concerning *managerial competences*, Airbnb providers are described as "amateur innkeepers" (Kreeger and Smith, 2017), "irrational" (Cai *et al.*, 2019), "inefficient" (Kwok and Xie, 2019), and "confused" (Hill, 2015). Hosts are micro-entrepreneurs (Stabrowski, 2017) with minimal business experience (Chen and Xie, 2017), not usually supported by benchmarking reports (Gibbs *et al.*, 2018b). In line with this profile, their ability to run their business is positively influenced by experience (variously called "membership" and/or "age") (Xie *et al.*, 2019). However, while the majority of hosts are mom-and-pop (also called "unprofessional" or "single listing"), there is a rising number of professional or commercial hosts, defined as Airbnb providers who manage more than one listing. These multiple-listing hosts are likely to be more skilled and structured than unprofessional hosts, considering the higher number of transactions they manage (Xie and Mao, 2017). The *contractual term* shows higher flexibility for Airbnb providers, who can choose when and where (in the case of multiple listings) to rent their property (Benítez-Aurioles,

2018), and, in many cases, can refuse clients (Karlsson *et al.*, 2017). The *economic variables* underlying the two business models are also different. A hotel entrepreneur needs to invest a lot of money, and running the business will sustain high operating costs, many of which are fixed. Airbnb providers use idle assets, and the business model is often described as near-to-zero marginal cost (Roma *et al.*, 2019). Furthermore, while hotels must respect numerous legal rules, P2P APs tend to operate in a grey legal area (Williams and Horodnic, 2017). In the case of hotels, price decisions are more rational and are based on revenue management techniques (including price discrimination and dynamic pricing), while, in the case of hosts, pricing is influenced by more subjective criteria and is less dynamic (Gibbs *et al.*, 2018b). However, the implementation of a machine learning approach in some paid P2P APs (as Airbnb) has partially changed this situation (Moreno-Izquierdo *et al.*, 2018). In the two cases, the *motivations* to be an entrepreneur are different. In both cases, economic gain plays a pivotal role (Karlsson and Dolnicar, 2016). However, in the case of Airbnb, social motivations are usually more relevant than with hotels (Alrawadieh and Alrawadieh, 2018). Finally, *relationships with guests* are described in diverse ways. Hotels are able to guarantee standard quality, according to their category, while, in the case of Airbnb providers, there is high variation in listing quality between hosts (Proserpio *et al.*, 2018). In P2P APs, the personal reputation of sellers is more relevant than in the hotel business, as is the so-called social interaction between host and guest (Abrate and Viglia, 2019), which has contributed to the slogan "live like a local" (Paulauskaite *et al.*, 2017).

Moving from the supply side to the demand side, there are at least three important differences in the attracted targets between Airbnb and hotels. P2P APs (and Airbnb, in particular) largely attract leisure clients, while business components are very marginal; hotels serve both segments (Young *et al.*, 2017; Sainaghi and Baggio, 2020). Airbnb guests often stay considerably longer than hotel guests (Varma *et al.*, 2016; Sainaghi, 2020a). Finally, the party size is considerably different and includes more people (especially friends), in the case of Airbnb (Poon and Huang, 2017).

Based on these variables, the substitution threat among all hotels and Airbnb listings in one destination area is expected to be limited.

Hypothesis 1. The substitution threat between all Airbnb providers and all hotels is limited.

While the first hypothesis compares Airbnb and hotels, the following four additional hypotheses focus on segments within each lodging supply (Airbnb and hotels). For Airbnb, as anticipated, a relevant segmentation concerns the number of listings managed. Studies on performance partially agree that single and multiple (host managing more than one property) hosts achieve different results (Koh *et al.*, 2019; Kwok and Xie, 2019; Moreno-Izquierdo *et al.*, 2019; Oskam *et al.*, 2018). There are some exceptions, especially when performance is measured using price (Tong and Gunter, 2020). Multiple hosts are usually included in one segment (called professional or commercial hosts). Few studies have adopted more fine-grained segmentation. An exception is the study of Deboosere *et al.* (2019), which distinguished between managing a single listing, two to ten listings, and more than ten listings. The current study segments hosts into five groups: i) hosts with a single listing, ii) hosts with two listings, iii) hosts with three listings, iv) hosts with four to ten listings, and v) hosts with more than ten listings. The segmentation is based on the different skills and competences required to manage the increasing number of listings and the business's organizational complexity. It is reasonable to assume that, from one to three listings, the business is mainly organized and managed by the host, with few external

collaborators. From four to ten, the business model changes and likely requires a division of labor and a partial specialization in different functions. Therefore, new competences are required. Finally, as suggested by Deboosere *et al.* (2019), ten is a new threshold of complexity and definitely initiates a more complex business model, centered around a team of workers who specialize in some functions (pricing, booking, housekeeping, information technology, customer relationship management, etc.). In the case of hotels, segmentation is based on the category, measured by classes. In particular, the three collapsed classes used by STR data are proposed, distinguishing between luxury and upper upscale, upscale and upper midscale, and midscale and economy. The long list of differences between Airbnb and hotels discussed to introduce the first hypothesis should generate a higher degree of synchronization within, rather than between, the two lodging supplies. Examples based on some of the previously-reported traits can explain this conclusion. The supply services (or supply attributes) are very different; pricing strategy is more structured in the case of hotels and more "naïve" for Airbnb hosts; and the attracted target (almost exclusively leisure guests for Airbnb, a wider market segment for hotels) shows limited overlap. Therefore, the similarity among Airbnb and hotels (within) is supposed to be higher than the synchronization between Airbnb and hotels. Within mutual information calculates the degree of similarity inside the five Airbnb groups and the three hotel classes. By contrast, between synchronization compares the five Airbnb groups (based on size) with the three hotels segments (based on classes).

Hypothesis 2. The within synchronization degree (for both Airbnb and hotels) is expected to be higher than the between synchronization degree.

Focusing on the between synchronization degree, a differentiated impact on hotel classes is expected, in line with some previous studies. For example, after segmenting hotels into five price levels (budget, economy, mid-price, upscale, and luxury), Zervas *et al.* (2017) found that the impact of Airbnb listings was progressively augmented moving down the price tiers. This is in line with disruptive theory, according to which Airbnb mainly affects low-end hotels (Guttentag, 2015). The study of Hajibaba and Dolnicar (2017) confirmed that cheaper hotels are more often substituted by P2P APs. Similar results were obtained by Guttentag and Smith (2017). These findings suggest higher substitution threat (mutual information) between all Airbnb listings and economy hotels and the opposite for the luxury segment. Upscale and upper midscale hotels should record a synchronization degree lower than economy and higher than luxury.

Hypothesis 3. Focusing on the between synchronization degree, the substitution threat generated by all Airbnb listings is higher for low-end (economy) hotels than for high-end (luxury) hotels.

Finally, a couple of additional hypotheses explore the substitution threat between hotel categories and Airbnb listings by considering the degree of host professionalization. As discussed above, reflecting on the *managerial competences* of Airbnb hots, the number of ranked listings (professional hosts) increases the host's experience, develops the business's complexity, and augments its organizational competences (Xie and Mao, 2017; Sainaghi *et al.*, 2020b; Sainaghi, 2020b). Not surprisingly, some studies reveal important differences in the business model of professional hosts compared to single hosts (Sainaghi and Baggio, 2020). In short, professional hosts are expected to compete more

intensely with hotels (hypothesis 4). Furthermore, as discussed when introducing the third hypothesis, the Airbnb business model is expected to be more synchronized to economy, rather than luxury, hotels. Therefore, the last hypothesis suggests a higher substitution degree between low-end hotels and the number of listings managed by Airbnb hosts (hypothesis 5). The following two hypotheses are therefore formulated.

Hypothesis 4. Focusing on all hotels, the substitution threat generated by Airbnb listings rises according to the number of rented listings (the degree of professionalization).

Hypothesis 5. The higher the number of listings managed by professional hosts, the higher the substitution threat with low-end (economy) hotels.

3. METHODOLOGY

The sample

This study tests the proposed hypotheses in two iconic locations in the Italian tourism market: Milan and Rome. Italy is a leading international tourism country, ranked fifth by the World Trade Organization in terms of arrivals, and ranked sixth for receipts. These two cities are the top Italian destinations. Milan and Rome have some differences in terms of strategic positioning. In fact, while Milan is the city where many financial institutions are headquartered and is, more generally, the center of economic life in Italy (Sainaghi and Mauri, 2018), Rome is the administrative capital, a top worldwide leisure destination, and the heart of Catholicism. The seasonal patterns of Milanese occupancy (the ratio between sold and available rooms for hotels and the ratio between booked and available properties for Airbnb listings) center more around midweek (panel A and C of Figure 1) and working days (panel D). These results are in line with many previous studies on this city (e.g., Baggio and Sainaghi, 2011; Sainaghi *et al.*, 2019b, 2019c). In the case of Rome, occupancy during weekend and holiday periods is higher than in Milan. In this analysis, the term "holiday" includes all weekends, civil and religious holidays (such as Christmas and Easter), and the entire month of August, due to the closure of many businesses, in line with similar previous studies (Sainaghi and Baggio, 2019b). The monthly seasonal patterns show a higher occupancy in Rome from May to October (panel B).

The decision to explore large cities is in line with many previous European studies, which analyzed the cities of Barcelona (Lambea Llop, 2017; Nofre *et al.*, 2018), Paris (Heo *et al.*, 2019), London (Ferreri and Sanyal, 2018), Venice (Oxoli *et al.*, 2017), and Berlin (Schäfer and Braun, 2016). Given the explorative goal of this study, the sample is limited to a couple of destinations. Many previous studies on the competition threat between Airbnb and hotels are based on single case studies (e.g., Zervas *et al.*, 2017).

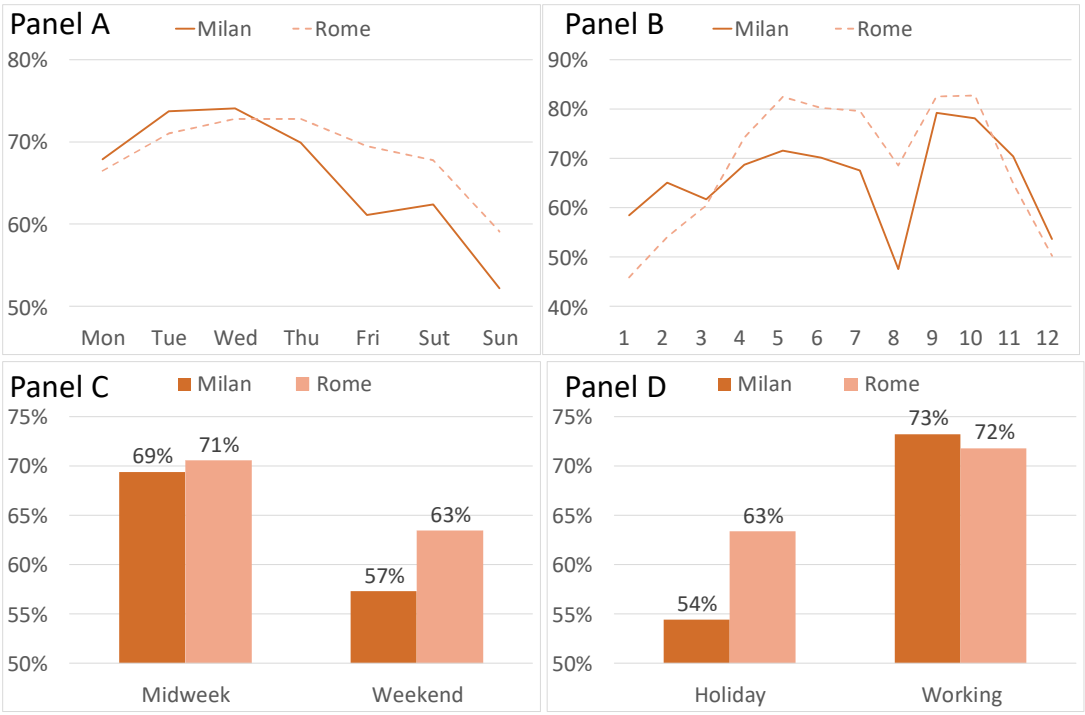

Figure 1. Weekly occupancy fluctuation in Milan and Rome (Source: Our analysis on STR data)

Focusing on data, two sources were used. For hotels, the daily data recorded by STR were employed, articulated per category. STR data includes the number of available rooms, revenue, and sold rooms. Although incomplete with regard to the available establishments, STR data cover about 34,000 rooms in Milan and 42,000 rooms in Rome, thus representing, for both destinations, a large portion of the entire population.

There are six registered categories, which, as anticipated, were collapsed into the following three categories: luxury and upper upscale, upscale and upper midscale, and midscale and economy. In other words, the STR data were received structured around six categories, but in order to reduce the complexity and improve the readability of the findings, the research team applied the synthetic (collapsed) categories, defined by STR. Therefore, these latter categories are not defined by the authors, but by STR. Many previous studies are based on STR data (i.e., Pan and Yang, 2017).

Concerning Airbnb, the rich data recorded by AirDNA were used. This third-party company scraped the listing data, accounting daily data for each listing, including available days, booked days, and price. Despite some differences between STR and AirDNA data (Agarwal *et al.*, 2019), many studies have used AirDNA information, especially in the field of listing performance (Dalir *et al.*, 2020; Gibbs *et al.*, 2018b; Gunter and Önder, 2018; Gunter *et al.*, 2020; Moreno-Izquierdo *et al.*, 2018; Yao *et al.*, 2019). As anticipated in the literature review, previous studies usually only distinguish between hosts with single (one) and multiple (more than one) listings. The work of Deboosere *et al.* (2019) proposed three categories for hosts (as reported in the literature review), while Sainaghi and Baggio (2020) proposed five. Considering that the majority of hosts in our sample manage one, two, or three listings, and that the rise from one to two and from two to three represents an important evolution of

the host business model, this study uses the five groups proposed by Sainaghi and Baggio (2020). The five groups are: i) hosts with a single listing, ii) hosts with two listings, iii) hosts with three listings, iv) hosts with four to ten listings, and v) hosts with more than ten listings.

This paper develops a longitudinal analysis, covering the period from January 2015 to March 2020 (the last available information when the analyses were carried out). This span of time is longer than the vast majority of previous studies focused on listing performance and competition (Cai *et al.*, 2019; García *et al.*, 2019; Ribes *et al.*, 2018).

The method

The use of time series in tourism has a long tradition, and some studies have employed large sets of data (e.g., Baggio and Sainaghi, 2016; Seabra *et al.*, 2020; Sainaghi and Baggio, 2017). Considering the different scale of hotels and Airbnb listings, this study focuses on occupancy rate. Occupancy rate is a relative measure defined as the ratio between sold and available rooms for hotels and as the ratio between booked and available properties for Airbnb listings. The use of occupancy rate has been employed in many previous analyses focused on hotels (Pan and Yang, 2017) and on P2P APs (i.e., Gunter and Önder, 2018; Oskam *et al.*, 2018). To estimate the similarity (and difference) between time series, in this study, the synchronization (de-synchronization) degree method was applied. The synchronization model was developed by Cazelles (2004) and applied to several studies (Akça and Yozgatlıgil, 2020; Freeman *et al.*, 2019; Zhao *et al.*, 2017). The process is structured around three steps: i) discretization, ii) mutual information, and iii) statistical significance estimation. Below, each step is presented and discussed.

The discretization activity transforms a time series in an ordered list of symbols, based on the comparison of two adjacent (neighboring) values. Given a time series $x(t)$, where x is the occupancy value measured at the t time, there are five possibilities: i) increase: $x(t) \leq x(t+1) < x(t+2)$, ii) decrease: $x(t+2) \leq x(t+1) < x(t)$, iii) stability: $x(t) = x(t+1) = x(t+2)$, iv) through point: $x(t+1) < x(t) \leq x(t+2)$ or $x(t+1) < x(t+2) \leq x(t)$, and v) peak point: $x(t) < x(t+2) \leq x(t+1)$ or $x(t+2) < x(t) \leq x(t+1)$ or $x(t+2) \leq x(t) < x(t+1)$. To each of these five cases, a corresponding letter is assigned; for this reason, this step is defined as discretization. At the end, therefore, the time series composed by values (occupancy rates, for this paper) is replaced by a series of letters. The discretization phase identifies the "rhythm" of the selected time series (rise, reduction, peak-up, peak-down, and stability).

The second step calculates the mutual information between the series that are compared. In this study, the mutual information was calculated by comparing the Airbnb and hotels series. Furthermore, this metric was calculated for all the pairs later reported in Figure 2 (see "Findings" section). As anticipated, this statistical measure identifies the similarity (and difference) among series that have the same temporal structures. This is, in short, a quantity that measures a relationship between two random variables that are sampled simultaneously and captures all dependencies between the variables (Latham and Roudi, 2009). The idea behind the mutual information is simple. This value captures whether the rhythm of the first time series is similar to the second. In this sense, the mutual information measures the synchronization. For example, if the series reach the same levels (increase, decrease, stability) and peaks (up and down), the mutual information is close to one, while, in the opposite case, the value is zero. For our purposes, a good similarity (synchronization) degree between

two series is considered a proxy for competition. Some examples help to clarify this statement. If both hotels and Airbnb listings have the same rhythm, it means that they serve similar segments, with similar seasonal patterns. This situation is supportive of competition threat between Airbnb and hotels. By contrast, if the seasonal patterns are quite different, implicitly, the attracted targets and seasonal trends are also different, and, therefore, the competition is low. Formally, given the series X (Airbnb) and Y (traditional hotels), the mutual information $I(X,Y)$ is calculated as: $I(X,Y) = H(X) + H(Y) - H(X,Y)$, where H is the entropy of each series $H(X) = -\sum p(x_i)\log_2(p(x_i))$, and $H(X,Y)$ the joint entropy of the series $H(X,Y) = -\sum\sum p(x_i,y_i)\log_2(p(x_i,y_i))$. We then normalize the mutual information using the formula $U(X,Y) = \frac{I(X,Y)}{H(X)+H(Y)}$. Thus, $U(X,Y)$ is in the interval [0,1]. It is easy to demonstrate that if X and Y are independent random variables, then $H(X,Y) = H(X) + H(Y)$; therefore, the mutual information is zero. For our use, this means that there is no synchronization of the two series (Latham and Roudi, 2009). All calculations were performed using an adapted version of the Python scripts available at https://github.com/people3k/pop-solar-sync.

The last step verifies the statistical significance of the values $U(X,Y)$ (in our case, the mutual information between Airbnb and hotels time series) that were previously calculated in the second step. Based on a Markov chain, a large number of random surrogate pairs are generated. The Markov chain preserves the structure of the original time series (with a one time-step memory) in the short-term. In order to verify whether the values obtained are statistically significant, we performed a *t*-test, considering, on one side, the mean mutual information between Airbnb and hotels and, on the other side, the surrogate time series obtained averaging the 500 random pairs.

4. FINDINGS

Figure 2 reports the findings. Panel A shows the mutual information for Milan, while Panel B focuses on Rome. The data are segmented for Airbnb providers (divided into five groups, based on the number of managed listings) and hotels (articulated in the three collapsed classes), plus the total for each lodging supply. The colors identify the within mutual information for Airbnb (light gray) and hotels (gray), while the white area focuses on between synchronization. All the values are highly significant. In order to interpret the number reported in Figure 2, the following threshold is used: i) if the value is less than 0.1, the degree of synchronization is very low, and, therefore, the time series can be considered de-synchronized or simply different, or ii) if the value is greater than 0.2, a good synchronization (or similarity) exists; the higher the value, the higher the similarity. These values may seem low, but the extreme sensitivity of the mutual information measure needs to be taken into account, and they are in line with other similar works (Freeman *et al.*, 2019; Sainaghi and Baggio, 2020).

The first hypothesis supposes that the substitution threat between *all* Airbnb providers and *all* hotels is limited. To test it, the overall mutual information between hotel and Airbnb data is considered. The value is equal to 0.087 for Milan and 0.117 for Rome. The slightly higher value for Rome is consistent with the city's positioning, which is more oriented to leisure. Leisure guests, as suggested in many previous studies (Guttentag, 2015; Varma *et al.*, 2016; Sainaghi, 2020a), represent the key segment for Airbnb. However, the value of mutual information clearly suggests a very limited overlap between

the two lodging segments. This result confirms the first hypothesis: The substitution threat among all the Airbnb providers and hotels is very limited.

The second hypothesis suggests that the within synchronization degree of Airbnb listings, on one side, and hotels, on the other, is higher than between synchronization. The within mutual information of Airbnb listings ranges from 0.217 to 0.438, in the case of Milan, considering the values among the five groups of hosts. In the city of Rome, the values are higher, ranging from 0.390 to 0.547. Overall, the values are supportive of a good (Milan) and very good (Rome) synchronization degree (similarity) between Airbnb hosts, segmented based on the number of rented listings. Moving to hotel classes (gray area of Figure 2), the values are considerably higher in the case of Milan, and range from 0.371 to 0.429. The city of Rome shows considerably lower values, moving between 0.154 and 0.236. The mutual information degree between Airbnb listings and hotels (white area) shows small values, usually less than 0.1 for both cities. These findings are supportive of the second hypothesis, which is almost a corollary of the first hypothesis. In fact, if Airbnb hosts and hotels are de-synchronized (first hypothesis), then the similarity is higher within each lodging segment (Airbnb on one side and hotels on the other), rather than comparing the two lodging offers (between synchronization).

The third hypothesis supposes higher competition between all Airbnb listings and economy (low-end) hotels, rather than luxury (high-end) hotels. To test this hypothesis, the between values are taken into consideration for both cities, focusing on the last line (all Airbnb supply) and the right (considering the three collapsed hotel categories). Starting from Milan, the mutual information is 0.078 (luxury and upper upscale), 0.075 (upscale and upper midscale), and 0.076 (midscale and economy). In the city of Rome, the values are very slightly higher: 0.100 (luxury), 0.087 (upscale), and 0.080 (economy). Generally speaking, the coefficients are always very small and, therefore, below the threshold of 0.2. Furthermore, there is not a clear increase in value when moving from luxury to economy; on the contrary, in both cities, the value reduces marginally. Therefore, the third hypothesis is rejected.

The fourth hypothesis focuses on all the hotels (penultimate line, “STR”) and evaluates the substitution degree, considering the scaling effect of Airbnb listings. The higher the professionalization (measured by the number of listings managed), the higher the competition, and vice versa. In the case of Milan, the degree of synchronization is always small and sufficiently stable (0.076 for single hosts, 0.073 for hosts with two listings, and 0.075 for hosts with more than ten listings). The results are similar in the case of Rome; hosts renting more than ten listings achieve a value of 0.098, which is lower than: i) mom-and-pop hosts (0.111), ii) hosts managing two listings (0.115), and iii) hosts renting out four to ten properties (0.108). These findings are not supportive of the fourth hypothesis.

Finally, the fifth hypothesis explores whether there is a “scaling” effect generated by Airbnb hosts on precise hotel classes. The hypothesis suggests that the higher the host’s degree of professionalization, the greater the substitution threat posed for low-end (economy) hotels. To test this hypothesis, the focus is on the center of Figure 2, on the left (white area). In Milan, the scaling effect produces very marginal variation in the mutual degree coefficients for all categories. For example, for luxury, the values are 0.066 (single listing), 0.073 (two listings), 0.062 (three listings), 0.050 (four to ten listings), and 0.072 (more than ten listings). This last coefficient (0.072) is the highest value, considering the between mutual information between hosts articulated by size and hotels segmented by class.

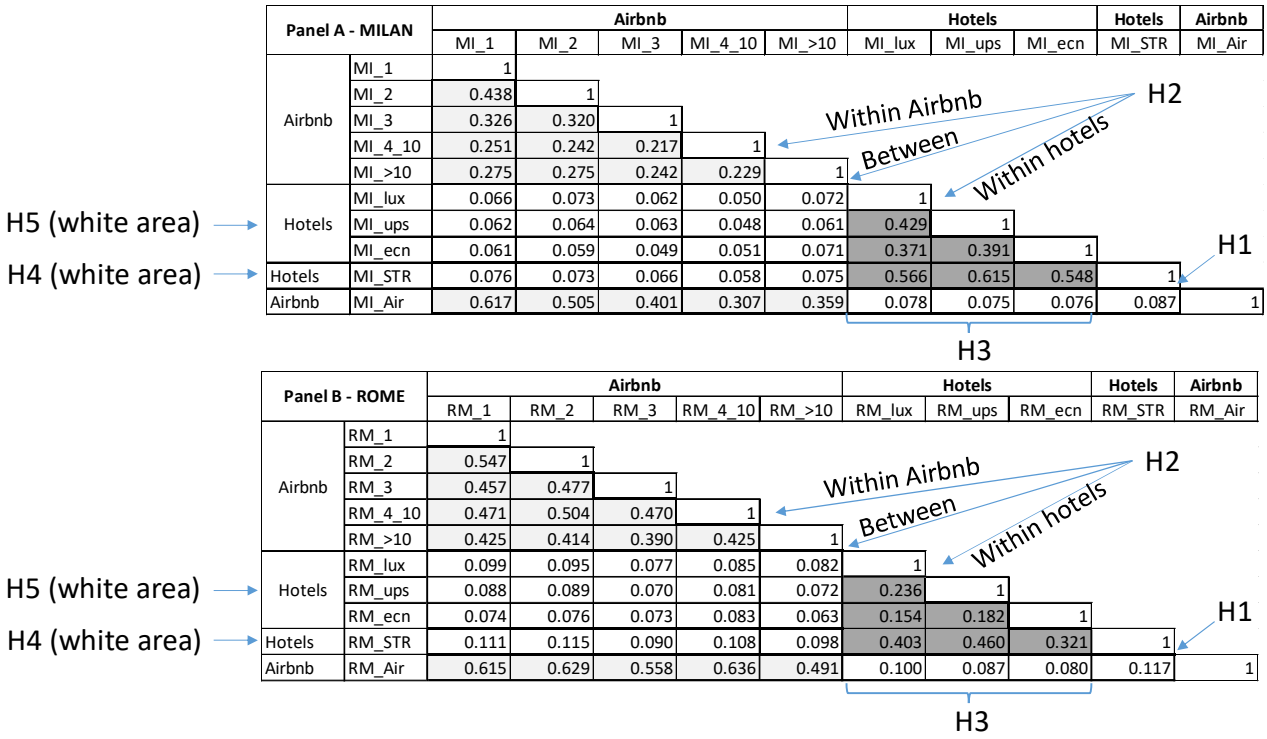

Figure 2. Mutual information analysis

Legend: MI = Milan; RM = Rome; 1 (single listing); 2 (two listings); 3 (three listings); 4–10 (from four to ten listings); >10 (more than ten listings); lux = luxury and upper upscale; ups = upscale and upper midscale; ecn = midscale and economy. STR = total of hotels. Air = total of Airbnb listings. Light-gray = within mutual information Airbnb. Gray = within mutual information hotels. White: between mutual information. H = hypothesis.

The degree of synchronization with economy hotels is generally lower than that of luxury. Hosts managing more than ten listings register the highest value (0.071); however, this value is lower than the threshold of 0.2. Regarding Rome, moving from left (mom-and-pop hosts) to right (professional hosts), the similarity reduces. Furthermore, the coefficients are slightly higher for luxury than for economy. The findings reject the fifth hypothesis.

The findings are supportive of the ability of these two lodging offers (Airbnb and hotels) to attract completely different segments, and they, therefore, show de-synchronized time series. Based on this result, an additional analysis was carried out to compare all listings and all hotels in the two cities (Table 1). The mutual information metric, which measures the degree of synchronization between Airbnb listings and hotels in the two cities (white area), is always small, much lower than the threshold of 0.2. Interestingly, the synchronization among similar series for the two cities accounts for a higher value: 0.286 for the Airbnb listings (light gray) and 0.281 for the hotels in Milan and Rome (gray). This finding is relevant because it confirms a higher similarity between the same supply segments in different cities (Airbnb (0.286) and hotels (0.281)), rather than the degree of synchronization between the different lodging segments in the same city (Airbnb and hotels in Milan (0.087) and in Rome (0.117)).

Table 1. The degree of synchronization between Airbnb listings and hotels in the two cities

		Milan (MI)		Rome (RM)	
		MI_Air	MI_STR	RM_Air	RM_STR
Milan	MI_Air	1			
	MI_STR	0.087	1		
Rome	RM_Air	0.286	0.107	1	
	RM_STR	0.067	0.281	0.117	1

Legend: STR = total of hotels. Air = total of Airbnb listings. Light-gray = within mutual information Airbnb. Gray = within mutual information hotels. White: between mutual information

5. DISCUSSION

Five hypotheses were tested and two of them were confirmed, as reported in Table 2. This study supports the limited substitution threat (and therefore the absence of direct competition) between Airbnb hosts and hotels (hypothesis 1). The findings also support the second hypothesis: the within synchronization among each lodging segment (Airbnb on one side, hotels on the other side) is higher than the between synchronization (comparison between Airbnb and hotels). The rejected hypotheses show that this study is not able to reveal higher competition between hosts and low-end hotels (hypothesis 3), an increasing competition generated by professional hosts on hotels (hypothesis 4) or low-end hotels (hypothesis 5).

Table 2. Hypotheses confirmation and rejection.

Hypotheses	Findings
1. The substitution threat between all Airbnb providers and all hotels is limited	Confirmed
2. The within synchronization degree (for both Airbnb and hotels) is expected to be higher than between synchronization degree	Confirmed
3. Focusing on between synchronization degree, the substitution threat generated by all Airbnb listings is higher for low-end (economy) hotels than for high-end (luxury) hotels	Rejected
4. Focusing on all hotels, the substitution threat generated by Airbnb listings rises according to the number of rented listings (the degree of professionalization)	Rejected
5. The higher the number of listings managed by professional hosts, the higher the substitution threat with low-end (economy) hotels	Rejected

These results suggest that applying a supply-side approach (as previously clarified), integrated considering the destination seasonal patterns, Airbnb hosts have broad differences in their occupancy time series, when compared to hotels. In this sense, the within synchronization is higher than the between synchronization. Focusing on between mutual information, the values are slightly higher in the city of Rome. This could be due to the stronger prevalence of leisure clients in the Italian capital, rather than in Milan, which is a very business-focused city. As revealed in the work of Sainaghi and Baggio (2020), the overlap between Airbnb hosts and hotels rises when a city attracts more leisure guests.

The rejection of hypothesis 3 is in line with the study by Dogru *et al.* (2019). The Airbnb formula does not generate a higher substitution threat to low-end (economy) hotels. This result can be explained by considering the differences between Airbnb and low-end hotels, which are summarized in the six points listed at the beginning of the literature review.

Finally, the rejection of hypotheses 4 and 5 (both related to the rising degree of host professionalization) suggests that the rising number of managed listings by one host does not change the substitution threat with traditional hotels. Increasing professionalization has more impact on the within synchronization, as described in the Figure 1, in both cities. This means that hosts managing many listings (for example the last group, more than ten) differentiate the occupancy trends, especially with respect to the three groups (hosts renting from one to three listings).

6. CONCLUSIONS

The conclusions are articulated in four sub-sections. Some theoretical and practical implications are traced. Finally, the main limitations of the study are identified and some possible research avenues are proposed.

Theoretical implications

This study sheds new light on the competition threat between Airbnb listings and hotels. It enriches the limited empirical literature on the impacts of Airbnb (and more generally of P2P APs on traditional hotels). As suggested by some authors (e.g., Dogru *et al.*, 2019), there are few current studies in this field, and they are mainly conceptual and/or descriptive. Furthermore, by developing a longitudinal approach, this study enlarges the temporal robustness of the evidence. Second, based on the degree of synchronization, the findings suggest an absence of direct competition between Airbnb and hotels in both cities. This conclusion focuses on the first and second hypotheses (both confirmed). Hotels and Airbnb listings appear in this study as two very separate markets; they attract different clients and, therefore, show only a marginal degree of synchronization. This is in line with some recently published papers that are discussed in the literature review. The findings are consistent in the two cities analyzed, Milan and Rome. Interestingly, there are more similarities between the seasonal occupancy series of Airbnb listings in Milan and Rome, on one side, and hotels in Milan and Rome, on the other, than between Airbnb and hotels in the same city. A third important theoretical consideration focuses on the method. The use of the synchronization degree method opens new possibilities for research on the substitution threat between Airbnb and hotels. The method represents a valid alternative to performance metrics correlations, which were used in some previous studies (i.e., Zervas *et al.*, 2017). Fourth, the study excludes stronger competition between Airbnb and low-end hotels. This can have deep implications for this field of research because it excludes the ability of Airbnb hosts to attract cheaper targets, similar to those served by economy or budget hotels. Fifth, the rising professionalization degree does not increase the substitution threat generated by Airbnb hosts. The latter shows an occupancy structure that remains disconnected (de-synchronized) from both low-end (hypothesis 4) and all hotels (hypothesis 5). The rising host professionalization degree influences synchronization more among Airbnb supply, partially differentiating the occupancy series between the first three groups (host managing from one to three listings) and the last group (host managing more than ten listings). This result sheds new light on future research focused on Airbnb hosts' business models and performance.

Practical implications

Some practical conclusions can be stated at the managerial and destination levels. At the managerial (firm) level, the study illustrates an absence of any substitution threat between Airbnb and hotels in both cities (hypotheses 1 and 2). This could have important consequences, especially for the pricing and revenue management policy. In fact, the higher the substitution threat, the higher the attention that Airbnb entrepreneurs should pay to the pricing strategy implemented by hotels, and vice versa. This conclusion can be extended to the three collapsed hotel classes, as well as the five groups of Airbnb providers. Interestingly, the findings show a progressive de-synchronization (within mutual information) among the five groups of Airbnb hosts, triggered by the rising professionalization degree. This result suggests the existence of a partial different business model for multi-listing hosts.

At the destination level, the findings can orient destination marketing and management organizations (Bornhorst *et al.*, 2010; d'Angella *et al.*, 2010; Sainaghi, 2006). Airbnb listings and hotels attract different targets, meaning that there is only marginal competition between the two. Therefore, destination managers can attract and integrate guests focused on hotels and Airbnb listings, in order to differentiate the destination commercial mix. Airbnb hosts are largely oriented on leisure targets. This point was discussed in the literature review, based on previous studies. Our findings simply reveal a limited substitution threat between Airbnb and hotels in both cities. Destination management organizations should, however, verify: i) the overall destination carrying capacity in order to avoid overtourism, ii) the coexistence between the two market segments (guest hosted by hotels and by Airbnb listings), and iii) the average tourist expenditure per guest, comparing travelers using Airbnb and hotels, especially if the destination has a high carrying capacity. Furthermore, caution is needed concerning the effects sometimes caused by Airbnb development on housing markets (Horn and Merante, 2017), local residents (Jordan and Moore, 2018) and workers (Fang *et al.*, 2016). In this study, the three rejected hypotheses exclude that hosts compete more against low-end hotels, the rising professionalization degree, or that Airbnb hosts increase the competition threat with hotels, in particular, with economy hotels.

Limitations

This is an explorative paper. Unlike previous studies focusing on competitive threats based on single case studies (Heo *et al.*, 2019; Zervas *et al.*, 2017), this present paper makes an important advancement by comparing two cities. However, the generalization of the findings remains partially limited. The longitudinal approach creates a consistent temporal pattern. The study ignores other relevant variables influencing the two lodging supplies (Airbnb and hotels), such as location, size, rating scores, and experience. The study compares two types of data (STR and AirDNA). The work carried out by Agarwal *et al.* (2019) suggests that the performance indicators—occupancy, average daily rate, and revenue per available room—are slightly different and, therefore, do not overlap perfectly. The analysis explores a long period of time without analyzing sub-seasonal periods; for example, the distinction between working and holiday periods. The paper is rooted in the supply-side approach. Some demand or market drivers are, therefore, omitted. The diffusion of Covid-19 has created a completely new market condition, characterized by a dramatic drop in demand. For example, the European report of STR revealed a reduction by more than 90% of revenue per available room in Italy between March and June 2020. The pandemic, and especially the post-Covid-19 period, could change the substitution threat between Airbnb listings and hotels. At the moment, it is very difficult to predict. These limitations could influence future research agendas.

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