The Host Canceled My Reservation! Impact of Host Cancelations on Occupancy Rate in the P2P Context: A Signaling Theory Perspective

Raffaele Filieri, Francesco Galati, and Elisabetta Raguseo

***Abstract*—The business of hosts in peer-to-peer (P2P) accommodation sharing has become an important source of revenue for individuals in many economies. However, there is a dearth of studies on hosts, specifically on the factors that affect host performance (i.e., occupancy rates). Drawing on the signaling theory and the source credibility theory and using a dataset of 41 610 reviews of 7004 Airbnb listings, we investigated the impact of cancelation rate—that conspicuously signals how many times a host has canceled a pre-existing reservation—on the host occupancy rate. Furthermore, we investigate the role of source credibility signals in reducing the impact of host cancelations. The results show that host signals of reputation, responsiveness, and expertise minimize the negative effect of cancelations on the occupancy rate. Theoretically, we advance the academic literature on credibility signals in P2P platforms and their moderating role on host performance. Managerially, the study helps P2P hosts in understanding the role of signals on occupancy rate.**

***Index Terms*—Airbnb, host cancelation, occupancy rate, peer-to-peer (P2P) accommodation, signaling theory.**

I. Introduction

The digitalization of markets, services, and products has fostered the rise of more agile firms, including digital peer-to-peer (P2P) business models [1]. This article focuses on P2P accommodation sharing (P2P-AS), which indicates the business of individuals renting a room, a house, or a flat that is facilitated by a digital platform in exchange for money for short-term stays. P2P-AS companies like Airbnb, Wimdu, Homeaway, and Couchsurfing are changing consumers' behavior and have created new challenges for the hospitality industry and public institutions [2]–[5]. The global relevance of the P2P-AS phenomenon has attracted the attention of academics. Research has been carried out to understand the impact of Airbnb on local communities, the economy, and traditional hospitality players (e.g., [6]–[8]). Scholars have also investigated consumers' motivations/intentions to use Airbnb (e.g., [2], [9]–[11]), consumer perceptions of hosts reliability and reputation [12]–[14], and the determinants of continuance [4] as well as of discontinuance intention [15].

Hence, most of the existing studies have focused on P2P customers (i.e., guests). However, only a few of them have studied the service provider [4], [11], [16]–[18] and specifically the determinants of P2P service providers' performance (i.e., occupancy rates). Airbnb hosts are entrepreneurs, and they are at the core of the Airbnb business model. The capacity of hosts to generate income and increase the occupancy rate of their accommodation depends on their selling skills and feedback, and the higher the income the host generates, the higher the profits of the sharing economy company.

According to signaling theory [19], [20], digital signals can help to reduce the transaction risks (e.g., [21]–[23]) and the information asymmetries existing between sellers and buyers in digital environments. Signaling theory suggests that buyers often adopt signals to provide for the lack of touch interaction, or information asymmetries, present in online transactions in the buyers' prepurchase stage [24]. Signals are particularly helpful in computer-mediated settings [22] and with services because consumers cannot handle, experience, or assess their quality before buying them (i.e., information asymmetry). Researchers have documented the prominent role of signals in influencing online leadership in social trading as well as increasing perceived trust and reduced risk in different online retail contexts [21], [22], [25]–[27] and electronic word-of-mouth (eWOM) settings (i.e., online consumer reviews in online travel communities [28], [29]).

This article focuses on the interaction between positive and negative signals about an Airbnb host and their impact on transaction performance (i.e., occupancy rate). In the P2P context, hosts can cancel their reservation at any time before guests' arrival. However, considering the high psychological, time, financial, and physical risks [30] that last-minute cancelations can cause, Airbnb displays, conspicuously, the number of times a host cancels his booking. Cancelations can be theoretically conceptualized in this article as negative signals [19], [20], which appear in the form of an automated message on the host page where guests leave their reviews. In this article, we argue that cancelations, which represent a negative signal, can potentially lower the level of trust toward an Airbnb host and deter

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consumers from booking a stay. Although the potential relevance of the cancelation signal in the transactions and economy of an Airbnb host, no research has conceptualized or investigated the 84 impact of this negative personal signal on a host's transaction performance (i.e., hosts' occupancy rate).

To fill this research gap, we integrate credibility theory [31] and signaling theory [19], and we argue that credibility signals used by Airbnb to communicate hosts' credibility (i.e., expertise and trustworthiness) could minimize, to some extent, the negative impact of host cancelations on consumers' intention to book the host's accommodation. Particularly in the sharing economy context, personal trust is an important currency [12], [32], and reputational capital is a crucial asset [14], [18], [33]. Signals about the service provider's credibility are of prominent importance in the sharing economy context, which is characterized by sharing valuable and personal goods and services between individuals who do not know each other and have never met before.

Signals about the host reputation can, *de facto*, reduce information asymmetries and risks in buyer–seller transactions [14], [34]. Airbnb adopts various signals about hosts' credibility. For instance, Airbnb provides signals about the potential reliability of Airbnb hosts, including signals of reputation, i.e., the badge level of the service provider (i.e., superhost); signals of host responsiveness, i.e., the host's response time; signals of host experience, i.e., the host's number of reviews (i.e., booked stays); and signals of host performance, i.e., the average host rating score. These signals can serve to increase the Airbnb guests' trust and confidence toward the source (i.e., Airbnb host) [14]. Hence, we contribute to the literature that considers source credibility as a moderator in consumers' behavior (e.g., [29], [35], and [36]) and transaction risk reduction signals for consumers in P2P electronic marketplaces [25]. This study has important managerial implications for P2P entrepreneurs.

II. Theoretical Background

A. Peer-to-Peer (P2P) Accommodation Literature Review

Digital platforms make it simpler for individuals to offer accommodation and other services to a global marketplace of consumers without setting up a website or needing to formalize their business [37]. Before the advent of online P2P-AS, the service of home-sharing and room rentals existed for a long time. Digital platforms now offer both the marketplace and payment systems, making it possible for individuals to offer accommodation directly to consumers without building a website, to collect payments directly, or to declare revenues to the tax office (e.g., [2] and [38]).

P2P-AS has attracted the attention of scholars. Empirical studies have focused on the impact of Airbnb listings on local communities and hotel's revenues and performance in various cities [6]–[8], [16] on the factors affecting perceived host trust [11], [12], trust toward the Airbnb platform [4], or the role of interaction between hosts and guests in building trust and reducing the negative impact of service failure [32]. Other studies have researched the determinants of pricing (e.g., [39]), the use of dynamic pricing strategies [40], the practice of racial price discrimination of some Airbnb hosts, and the motives behind consumers' decision to share goods and services [2], [9]. Other studies use big data to explore Airbnb guest's experience (e.g., [41]), the criteria that need to be fulfilled to obtain the Airbnb superhost badge [42], as well as discontinuance intention [15].

However, research on the determinants of Airbnb host's transaction performance is still limited [14]. Specifically, there is a dearth of research on how negative signals, such as Airbnb hosts' cancelations, affect the host's transaction performance, which, in the hospitality context, is measured by occupancy rates [43]. Occupancy is a performance variable of paramount importance in the service sector due to the perishable nature of services [44], and, compared to other performance measures, using this performance measure allows the researchers to assess the elasticity between this volume dimension and a variation of prices [43]. Below, we discuss the theoretical underpinning of our study.

B. Signaling Theory and Risks in the P2P Accommodation Sharing Industry

In his seminal work, Spence [19] discussed the information asymmetries present in the job market and specifically when employers have to evaluate job candidates' quality. In this context, the employer does not personally know the job applicant and, hence, has limited information to assess his/her future performance. The job applicant can use some signals to convey information about his/her skills and capabilities [19], such as the education level, previous job experience, or jobs in nonprofit organizations. This information can serve as a signal of the quality and personality of the candidate, which helps the recruiter to reduce information asymmetry and select the best candidates.

Signaling theory has been adopted as a framework in various business disciplines to understand how buyers and sellers deal with limited or hidden information in pretransactional (prepurchase) contexts [24]. The central tenet of signaling theory consists in explaining the various types of signals and the situations in which they are used [20], [22]. Signals provide observable information about unobservable elements [45]. Consumers, in turn, receive and interpret signals before responding to them [46].

Due to the lack of physical copresence of sellers and buyers in computer-mediated settings, signaling theory has often been adopted in these contexts [29]. Scholars have demonstrated that various types of signals, including brand equity [47], performance and popularity [48], trader credentials, trading volume, performance, and risk [49], price [50], seals of approval, return policy, security disclosures, privacy disclosures, and awards from neutral sources [26], warranty, advertising [51], and certificates [52], influence various aspects of consumer behavior including network leadership in online social trading [49], perceived trustworthiness and risk in transactions with online retailers or other organizations (i.e., banks) [21], [22], [25]–[27].

Indeed, signals are more relevant in digital contexts than offline ones [25] due to the higher information asymmetries present between sellers and buyers [22]. Information asymmetry refers to the different amounts of information detained by two individuals involved in an exchange, be it a transaction or simply communication. In business environments, signals are often adopted to communicate the quality of products and services that are generally difficult to evaluate due to information asymmetries [20].

Signals are particularly important in situations of high risk and uncertainty [50], [51], [53], [54], such as in the P2P accommodation context (i.e., Airbnb) [55]. In this context, the host cancelation signal represents a visible, automated message that appears on the host page when hosts cancel a reservation. Cancelations increase the perception of the inconvenience of P2P bookings and increase the effort on the part of the user [15]. Cancelations can increase the uncertainty and risks of the P2P accommodation context compared, for example, to the hotel sector [56]. The hospitality industry adopts well-established and internationally recognized signals certified by authoritative sources and visually represented as the number of stars [57]. Conversely, in the P2P accommodation sector, certifications are missing, and ratings, where present, are assigned by single customers and not by industry experts. Hence, consumers may find it more challenging to evaluate the (seller) products' reliability and quality in the P2P context, creating uncertainty and risks for potential customers. Compared to hotels, P2P hosts offer a service that is nonstandardized, deregulated, and volatile. The *Airbnb hell*'s website and other similar platforms offer uncensored "horror" stories from Airbnb hosts and guests, which reflect the variety of risks present in the P2P-AS industry. In addition, Airbnb hosts offer services, which are characterized by intangibility, variability, perishability, and inseparability, whose characteristics make services more difficult to evaluate prior to purchase than goods [58]. Furthermore, Airbnb hosts are not professionals but individuals who have decided to rent a room or sometimes even their couch to make an extra income [4], and they rarely receive training before starting to run their business. Therefore, there is a risk related to the level of expertise of the service provider. In summary, the Airbnb context is characterized by high levels of risk and by information asymmetries.

In the sharing economy context, the development of trust is a fundamental marketing task for Airbnb "entrepreneurs" [2], [12]. To reduce risks, Airbnb uses specific signals that can increase cognition-based trust toward the host, which makes signaling theory [19] particularly suitable to answer our research question. McAllister [59] identified two types of trust: affect-based trust and cognition-based trust, where the former refers to the "emotional bonds between individuals" that are grounded upon expressions of "genuine care and concern for the welfare" of the other party, while cognition-based trust is based upon individual beliefs about the other party's reliability and dependability [59, p. 26]. In the Airbnb context, signals can help to develop cognition-based trust toward hosts. Cognition-based trust is communicated by the perceived credibility of the service provider. Source credibility generally includes two dimensions: trustworthiness and expertise [31]. The expertise dimension is more likely to develop cognition-based trust, which smoothens risk-taking behavior in uncertain circumstances as it can reduce the costs required to interact with others and monitor their behavior, labeled as transaction and searching costs [60], [61].

Hence, signals act as cues of the host credibility, which, as Belk [34] confirms, are a proper way to build trust in collaborative consumption contexts. Airbnb provides positive source credibility signals, namely signals that attempt to communicate the experience and reliability of the host, i.e., the signals of reputation (i.e., "superhost" badge), signals of host responsiveness, i.e., the response time, signals of host experience, i.e., the host's number of reviews, and signals of host performance, i.e., the average rating score.

III. Hypotheses Development

A. Cancelation Signals and Occupancy Rate

The cancelation signal is represented by an automated message that appears on the host listing every time the host cancels a reservation. Cancelation signals cannot be removed and they communicate the host's unilateral decisions to delete one or more reservations. As mentioned above, the cancelation of a reservation is one of Airbnb guests' risks. Airbnb hosts are not professional operators in the travel and tourism industry. Rather, they often have other jobs, they do not host guests at all times, and they do not have staff to replace them when they are absent. Therefore, host's cancelation of a guest's reservation, even sometime after booking acceptance, is likely. Cancelations can disrupt guests' travel plans and impact confidence and trust toward the Airbnb platform and its community. Research shows that trust toward the Airbnb host and platform is fundamental to motivate travelers to purchase a P2P accommodation [4], [12] and to enhance hosts' intention to continue using the platforms in the future [4], [32].

Cancelations can occur at different points in time and even when the trip occurs. As such, host cancelations pose economic, time, and psychological risks [62]. First, when the host cancels a booking, the guest has to spend some time seeking an alternative place to stay that suits his/her needs. As time goes by, in many destinations, the availability of Airbnb accommodation tends to decrease while the price of the alternatives left tends to rise. This situation would lead guests to fewer options and higher psychological stress. Identifying a new accommodation solution requires additional time, cognitive efforts, and stress due to having to find a new agreement with other hosts rapidly. According to the cognitive miser perspective [63], these additional efforts are undesirable for people, as the human mind often seeks to avoid computational efforts. Information search and acquisition costs play an important role in influencing customer purchase decisions in the sharing economy. In this context, consumers tend to prefer less expensive solutions in terms of transaction costs [64]. Cancelation signals on Airbnb make potential customers ponder that, if cancelations occur, they will need to identify a different suboptimal solution, which would be more expensive and/or less desirable. By combining these arguments with the risk aversion perspective (e.g., [65]), we argue that people prefer safe outcomes over risky ones of equal or higher value. In the accommodation P2P context, this means that consumers could be less prone to book a risky option, i.e., a P2P accommodation with cancelations. Drawing upon these arguments, we hypothesize:

H1: The higher the host cancelations, the lower the occupancy rate.

B. Host Reputation Signal

Profile characteristics are the main source of personal reputation about service (and goods) providers in P2P contexts [14]. One of the earliest and best-known online reputation systems is run by eBay [66], which developed a star-shaped feedback symbol used by buyers to rate sellers' reliability and product quality. In the travel and tourism sector, user-generated content platforms such as TripAdvisor and Yelp introduced the badge system or elite awards to communicate to other users the reputation of their reviewers of restaurant and accommodation, which is effective in determining restaurant review helpfulness [67]. Airbnb adopts a different reputation system and only for hosts, i.e., the "Superhost" badge. Superhosts are generally hosts who put a higher effort compared to other hosts in their business [68].

Research has demonstrated that hosts who display a superhost badge are more likely to receive reviews and higher ratings [68]. The superhost badge is a signal that synthesizes the online reputation of the host, which creates a perception of reliability among the potential customers and can increase consumers' intention to book the host's accommodation. Furthermore, the people-to-people transmission of reputation signals can deter moral hazard in markets where players repeat transactions but rarely with the same player [66]. Hence, we expect that the higher reputation of superhosts can reduce the negative effect of cancelations on their profile. Thus, we hypothesize:

H2: Being a superhost reduces the negative effect of cancelations on the occupancy rate.

C. Host Responsiveness Signal

Responsiveness is a concept often adopted as a performance metric in the supply-chain context and is defined as the ability to react purposefully and within an appropriate time-scale to customer demand or changes in the marketplace, to bring about or maintain competitive advantage [69], [70]. In the Airbnb context, guests can ask hosts (before booking) about different aspects of the service, such as check-in and check-out issues and timing, detailed addresses, distance to public transportation, events, and the like. However, responding to guests' information requests is not mandatory for hosts, though the literature suggests that it is worthwhile to take care of guests' concerns in terms of interactions (e.g., [32], [56], and [71]–[73]). More in detail, a high response rate and quick response can signal a hospitable attitude [73], which signal social presence [74], and demonstrate their willingness to be held accountable for their actions, which may improve hosts' trustworthiness [56], [71]–[73]. In the sharing economy environment, hosts' communication is an evaluation criterion for assessing service quality [75].

Furthermore, the response speed is also important, as a quick response can signal hosts' efficiency and enthusiasm and reduce perceived risks. Research in a service failure and recovery scenario context has demonstrated that host–guest interaction increases trust in the host [32]. Rapid replies are important in the prebooking phase too. When hosts answer guests' doubts and questions in a timely fashion, they demonstrate that they genuinely care and are concerned for the welfare of the other party, namely affect-based trust [59, p. 26].

The host's responsiveness can also communicate empathy, affiliation, and rapport based on shared regard for the other person [76], and it demonstrates that the host agrees to rent the house/room [56]. Based on the above arguments, we expect that high host responsiveness can reduce the negative effect of cancelations on the occupancy rate. Thus, we hypothesize:

H3: The higher the host responsiveness, the lower the negative effect of cancelations on the occupancy rate.

D. Host Experience Signal

Host experience refers, in this study, to the number of reviews obtained by the host, which indicates the number of times a host has been hosting guests and, hence, his experience in the digital P2P accommodation business. Experienced hosts have generally hosted many guests and, thus, are expected to have developed significant hospitality knowledge [77]. Expertise develops with experience, and the longer the platform's usage, the higher the number of reviews received, the higher would be the expected expertise of the host. Furthermore, the number of reviews received can indicate the proficiency and familiarity of the host with Airbnb rules and regulations (i.e., "how Airbnb works"). Thus, higher experience in using the platforms corresponds to better marketing skills, knowledge of the hospitality industry, and of the needs of Airbnb guests.

Research in eWOM shows that consumers perceive as high performing and of higher quality the products/services that receive many reviews [28], [78], [79]. The number or volume of reviews posted by a reviewer indicates his/her expertise and influences the helpfulness and diagnosticity of information [28], [77]. Moreover, the number of reviews for each hotel is a signal that provides information about the popularity of the hotel [28]. In research on online social trading, trading volume per month sends positive signals about the investment opportunities and the trader's commitment to trading [49]. Drawing on the arguments, we expect that the number of reviews—a signal of host experience—can reduce the risk embedded in the likelihood of cancelation. Hence, we hypothesize as follows:

H4: The higher the host experience, the lower the negative effect of cancelations on the occupancy rate.

E. Host Performance Signal

Host performance refers to the numerical visual signals regarding the overall level of satisfaction (i.e., average evaluation) expressed by all guests who have visited, reviewed, and rated the host's accommodation. Performance signals are visual scores about the average guests' evaluation; they are sometimes represented with star or bubble symbols and sometimes come in numerical form, often ranging from one to five (e.g., Airbnb, TripAdvisor, and many more) [80]. According to the marketing and social sciences literature, consumer aggregate ratings are a form of normative influence, as they communicate the behavior of a crowd of customers [80]. To reduce risks, consumers follow

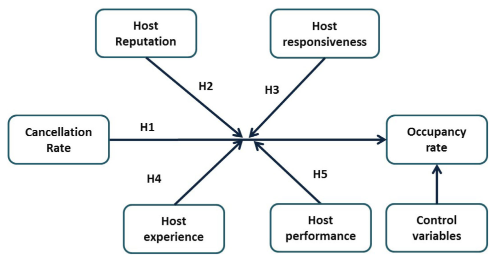

Fig. 1. Research framework and hypotheses.

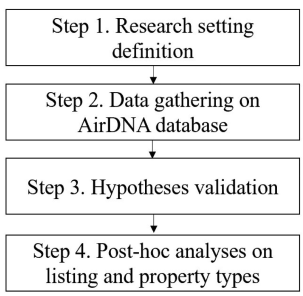

Fig. 2. Steps followed in the research process.

other consumers' recommendations made available over the Internet in the form of aggregated ratings (e.g., [81]).

The performance signal is an influential signal because it exerts a significant influence on consumers' intentions and behavior [81]–[83], and it affects hotels' pricing strategy [84]. Moreover, overall ratings represent easy-to-evaluate base-rate information [85], which indicates a summary of how well or bad a service provider (i.e., host) is doing based on all the reviewers' averaged evaluation, namely its performance. This signal can facilitate consumer evaluation, especially when consumers face similar product alternatives [80], which is often the case in P2P accommodation available in a destination. In line with the cognitive miser perspective [63], people tend to take shortcuts when making decisions and rely on available informational cues. Based on these arguments, we hypothesize as follows:

H5: The higher the host performance, the lower is the negative effect of cancelation rate on occupancy rate.

Fig. 1 shows the research framework and the hypotheses in this study.

IV. Methodology

A. Dataset and Sample

We choose London as the research setting for various reasons. London is the capital city of a destination included among the Top 10 world tourism destinations [86] and is the first destination in Europe [87], with Europe being the leading continent in terms of international tourism arrivals [86]. The data selection and analysis process is shown in Fig. 2. Airbnb data were purchased from AirDNA, a company that tracks the performance data of 10 million Airbnb and Vrbo vacation rentals in many global markets. We then created a dataset composed of 41 610 reviews of 7004 Airbnb listings in London in 2019. The selected sample only included Airbnb rentals with at least one booked night. The final dataset was based on monthly based observations.

TABLE I
Variable Operationalization

Variable	Operationalization
Dep. variable	
Occupancy rate	Total Booked Days / (Total Booked Days + Total Available Days)
Ind. variables	
Cancellation rate (CR)	Total number of cancelled reservations
Host reputation (HRP)	Superhost badge (Dummy variable equal to 1 for superhost, 0 for all other host types)
Host responsiveness (HRS)	Lagged and log percentage of new inquiries and reservation requests a host responded to within 24 hours
Host experience (HE)	Lagged and log sum of the total number of reviews received by the host
Host performance (HP)	Lagged overall host's rating
Control variables	
Month	Dummy variables for month
Property type	Dummy variables for property type
Listing type	Dummy variables for listing type
Neighbourhood	Dummy variables for neighborhood

1) Constructs Operationalization: Occupancy rate: The dependent variable in our study represents the occupancy rate of each listing on a monthly basis for the year 2019. We calculated occupancy rate as follows: Total Booked Days/(Total Booked Days + Total Available Days).

Number of canceled reservations: The independent variable in our study was measured by calculating the monthly number of reservations canceled by each host.

Host reputation: It refers to the reputation of the host. In the Airbnb context, the superhost badge indicates a host with a high reputation [13], [14]. The variable is a dummy variable that equals 1 when the host is a superhost and 0 otherwise.

Host responsiveness: It is measured by calculating the percentage of new inquiries and reservation requests a host has responded to (by either accepting/preapproving or declining) within 24 h. Given its shape, we computed the logarithmic form of the response rate, and we lagged to understand the impact of this variable on the host occupancy rate of the following month.

Host experience: It indicates the total number of reviews received by a host. Given its shape, it was computed the logarithmic form of the response rate and was lagged to understand its impact on the occupancy rate of the following month.

Host performance: It represents the lagged overall rating of a host listing on a scale from 1 to 5. The host performance measure was lagged to understand its impact on the host occupancy rate of the following month.

We also included some relevant control variables like month, property type, listing type, and neighborhood. A list of dummy variables was included in the model for controlling for the month the observation refers to the property type of every listing (e.g., private room, apartment, and the like), listing type (i.e., private room, entire home, and shared room), and neighborhood. Table I shows the list of variables and their operationalization.

TABLE II
DESCRIPTIVE STATISTICS

Variable	Mean	St. Dev.	Min	Max
Dep. Variable				
Occupancy rate	0.701	0.287	0	1
Ind. Variables				
CR	0.055	0.260	0	6
HRP	0.420	0.493	0	1
HRS (lagged and log)	4.559	0.344	0	4.615
HE (lagged and log)	0.902	0.318	0.693	2.890
HP (lagged)	4.703	0.248	1	5
Control variables	N. dummies			
Month	12			
Property type	29			
Listing type	3			
Neighborhood	33			

TABLE III
REGRESSION MODEL RESULTS

Ind. Variable	Occupancy rate					
Model	*M1*	*M2*	*M3*	*M4*	*M5*	*M6*
Hypothesis		*H1*	*H2*	*H3*	*H4*	*H5*
Direct effects						
HRP	0.023***	0.022**	0.021**	0.095	0.021**	0.022**
	(0.009)	(0.009)	(0.009)	(0.062)	(0.009)	(0.008)
HRS	0.043***	0.043***	0.043***	-0.039*	0.043***	0.043***
	(0.014)	(0.014)	(0.014)	(0.024)	(0.014)	(0.014)
HE	0.034***	0.035***	0.035***	0.144***	0.057***	0.057***
	(0.005)	(0.005)	(0.005)	(0.047)	(0.005)	(0.005)
HP	-0.007	-0.006	-0.006	0.007	-0.003	-0.005
	(0.020)	(0.020)	(0.020)	(0.074)	(0.019)	(0.020)
CR	…	-0.016**	-0.019*	-1.077**	-0.078**	-0.079*
	…	(0.010)	(0.011)	(0.542)	(0.033)	(0.201)
Moderating effects						
CRxHRP	…	…	0.097**	…	…	…
	…	…	(0.042)	…	…	…
CRxHRS	…	…	…	0.220**	…	…
	…	…	…	(0.120)	…	…
CRxHE	…	…	…	…	0.058**	…
	…	…	…	…	(0.025)	…
CRxHP	…	…	…	…	…	0.015
	…	…	…	…	…	(0.043)
Constant	0.502***	0.499***	0.498***	1.063***	0.470***	0.475***
	(0.132)	-0.132	(0.132)	(0.341)	(0.132)	(0.132)
R squared	9.60%	10.80%	10.83%	11.58%	11.71%	11.65%
Hp supported?		*Yes*	*Yes*	*Yes*	*Yes*	*No*

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Robust standard errors in parentheses; control variables that refer to the dummy variables of the months, the dummy variables of the neighborhoods where every Airbnb listing is located, and the listing-type dummies are omitted.

V. FINDINGS

A. Descriptive Statistics

Table II shows the mean, standard deviation, minimum, and maximum of every variable in our framework, as well as the month, property types, listing types, and neighborhood of the 7004 listings located in London. Overall, the listings in 2019 have an average occupancy rate of 70.10%.

Table II shows that the number of canceled reservations is lower compared to all reservations while the response rate is higher, demonstrating a high involvement of the hosts in the interaction with their guests. 42% of the hosts in our sample display the superhost badge. At the same time, the host performance signal is skewed since the mean value is very close to the maximum value.

The Appendix shows statistics about the distribution of listings in our sample based on the property type. Most listings, i.e., 64.2%, are apartments, 20.1% are houses, while 7% are townhouses (Appendix - Table VI). Considering the listing type, more than half of our sample comprises entire homes. Half of them are private rooms, while only 0.5% includes other listing types (Appendix - Table VII). Finally, the Appendix shows the distribution of listings according to their localization in London (Appendix - Table VIII). Most listings, namely the 9.79%, are located in Westminster, while the other neighborhoods with a high density of Airbnb listings are Hackney, Tower Hamlets, Lambeth, and Camden, demonstrating a homogenous distribution of Airbnb in London. The Appendix also provides further details about the descriptive statistics of the sample used in this study (Appendix - Table IX, Table X, Table XI and Table XII).

B. Hypotheses Testing

Before validating the study's hypotheses, Hausman's specification test was conducted to establish the appropriateness of a fixed-effect model over a random effect model. The results of the test highlight the suitability of the random effect model. We then computed the variance inflation factor (VIF)s to assess potential multicollinearity problems. Since the variables have adequate VIFs, well below the suggested threshold of 10 (Greene, 2003), multicollinearity was not an issue.

We run regression analysis to test the five hypotheses in this study (see Table III).

In Model 1, we included all the independent variables and the control variables, with the only exception of the number of cancelations. In Model 2, we added the number of cancelations to test Hypothesis 1. From Model 3 to Model 6, we included, in every model, one different interaction term between the number of canceled reservations and respectively host reputation (i.e., superhost badge), host responsiveness (i.e., response rate), host experience (i.e., number of reviews), and host performance (i.e., overall rating).

We tested the first hypothesis with the formulation of the following equation:

$$\begin{aligned} &Occupancy\,rate_i = a_1 + b_1 Superhost_i \\ &+b_2 Response\,rate_i + b_3 Number\,of\,reviews_i \\ &+b_4 Overall\,rating_i + b_5 Number\,of\,canceled \\ &reservations_i + \sum \mathrm{cv}_i + \varepsilon_i \end{aligned} \tag{1}$$

where i refers to the listing, $\Sigma \mathrm{cv}_i$ refers to the sum of the control variables, and ε_i is the error term. Model 2 shows a negative and statistically significant relationship between cancelation numbers and occupancy rates. Thus, hypothesis 1 is supported. Model 3 supports that the interaction between host reputation and the number of canceled reservations is positive and statistically significant, highlighting a positive moderation effect (H2). The interaction term coefficient of the number of canceled reservations and the host responsiveness is statistically significant and positive (see Model 4, H3), highlighting

TABLE IV
REGRESSION MODELS (LISTING TYPE: ENTIRE HOME; PRIVATE ROOM)

Ind. Variable	Occupancy rate							
Model	*M7*	*M8*	*M9*	*M10*	*M11*	*M12*	*M13*	*M14*
Direct effects								
HRP	0.032**	0.016	0.045	0.146	0.031**	0.016	0.033**	0.016
	(0.013)	(0.012)	(0.100)	(0.146)	(0.013)	(0.012)	(0.013)	(0.012)
HRS	0.013	0.105***	-0.029	-0.007	0.014	0.103***	0.013	0.103***
	(0.013)	(0.026)	(0.037)	(0.202)	(0.013)	(0.026)	(0.013)	(0.026)
HE	0.052***	0.030***	0.142*	0.072	0.067***	0.054***	0.068***	0.054***
	(0.010)	(0.005)	(0.076)	(0.086)	(0.011)	(0.006)	(0.011)	(0.006)
HP	0.037	-0.043	-0.025	-0.065	0.040	-0.041	0.040	-0.041
	(0.027)	(0.029)	(0.109)	(0.146)	(0.027)	(0.029)	(0.027)	(0.029)
CR	-0.023	-0.016	-1.157*	0.063	-0.100**	-0.048	0.047	-0.048
	(0.015)	(0.016)	(0.641)	(3.956)	(0.045)	(0.051)	(0.285)	(0.051)
Moderating effects								
CRxHRP	0.031	0.114***	…	…	…	…	…	…
	(0.058)	(0.028)	…	…	…	…	…	…
CRxHRS	…	…	0.246**	-0.054	…	…	…	…
	…	…	(0.143)	(0.874)	…	…	…	…
CRxHE	…	…	…	…	0.072**	0.036	…	…
	…	…	…	…	(0.033)	(0.044)	…	…
CRxHP	…	…	…	…	…	…	-0.013	0.036
	…	…	…	…	…	…	(0.061)	(0.044)
Constant	0.106	0	0.081	1.297	0.074	0	0.075	0
	(0.142)	(0)	(0.544)	(1.227)	(0.141)	(0)	(0.142)	(0)
R-squared	10.47%	13.41%	11.51%	10.77%	10.94%	14.42%	10.86%	14.40%
Listing type								
Entire home	x		x		x		x	
Private room		x		x		x		x

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Robust standard errors in parentheses; control variables that refer to the dummy variables of the months, the dummy variables of the neighborhoods where every Airbnb listing is located, and the property-type dummies are omitted.

TABLE V
REGRESSION MODELS (PROPERTY TYPE: APARTMENT, HOUSE, AND TOWNHOUSE)

Ind. Variable	Occupancy rate											
Model	*M15*	*M16*	*M17*	*M18*	*M19*	*M20*	*M21*	*M22*	*M23*	*M24*	*M25*	*M26*
Direct effects												
HRP	0.024**	0.034	0.043	0.026	0.160	0.037*	0.024**	0.034	0.043	0.026**	0.034	0.043
	(0.011)	(0.022)	(0.029)	(0.080)	(0.698)	(0.019)	(0.011)	(0.021)	(0.030)	(0.011)	(0.021)	(0.030)
HRS	0.038**	0.068*	-0.017	-0.031	0.806	-0.003	0.038**	0.067*	-0.016	0.038**	0.067*	-0.016
	(0.017)	(0.035)	(0.029)	(0.024)	(1.344)	(0.042)	(0.017)	(0.035)	(0.026)	(0.017)	(0.035)	(0.026)
HE	0.035***	0.023**	0.041**	0.114**	0.306	0.072***	0.056***	0.068***	0.036**	0.056***	0.068***	0.036**
	(0.006)	(0.010)	(0.016)	(0.055)	(0.259)	(0.018)	(0.007)	(0.012)	(0.016)	(0.007)	(0.012)	(0.016)
HP	0.031	-0.086	-0.058	0.064	-0.201	-0.104**	0.033	-0.083	-0.053	0.028	-0.083	-0.053
	(0.023)	(0.055)	(0.079)	(0.095)	(0.296)	(0.043)	(0.023)	(0.054)	(0.079)	(0.023)	(0.054)	(0.079)
CR	-0.013	-0.005	-0.063	-1.003**	1.258	-5.576***	-0.061	-0.044	-0.375*	-0.396	-0.044	-0.375*
	(0.013)	(0.028)	(0.058)	(0.509)	(1.920)	(1.816)	(0.038)	(0.087)	(0.210)	(0.274)	(0.087)	(0.210)
Moderating effects												
CRxHRP	0.040	0.220***	0.195***	…	…	…	…	…	…	…	…	…
	(0.064)	(0.058)	(0.065)	…	…	…	…	…	…	…	…	…
CRxHRS	…	…	…	0.205**	-0.299	1.201***	…	…	…	…	…	…
	…	…	…	(0.114)	(3.537)	(0.396)	…	…	…	…	…	…
CRxHE	…	…	…	…	…	…	0.049*	0.042	0.308**	…	…	…
	…	…	…	…	…	…	(0.029)	(0.081)	(0.167)	…	…	…
CRxHP	…	…	…	…	…	…	…	…	…	0.084	0.042	0.308
	…	…	…	…	…	…	…	…	…	(0.059)	(0.081)	(0.167)
Constant	0.321**	0	0.880**	0.767*	-2.691	0.702**	0.293*	0.778**	0	0.317**	0.778**	0
	(0.153)	(0)	(0.376)	(0.421)	(5.819)	(0.293)	(0.153)	(0.302)	(0)	(0.154)	(0.302)	(0)
R-squared	9.16%	12.00%	20.67%	22.43%	15.80%	19.51%	9.90%	13.96%	20.68%	9.93%	14.01%	20.37%
Property type												
Apartment	x			x			x			x		
House		x			x			x			x	
Townhouse			x			x			x			x

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; Robust standard errors in parentheses; control variables that refer to the dummy variables of the months, the dummy variables of the neighborhoods where every Airbnb listing is located, and the listing-type dummies are omitted.

the importance of the host responsiveness in interacting with consumers. Findings show that the host performance does not have any moderating effect. Hence, we cannot support H5.

C. Post Hoc *Analyses*

Since our sample included different listings and property types, we conducted two *post hoc* analyses (Tables IV and V) to test whether the hypotheses are supported in the different contexts in terms of listing and property types. In Table IV, we investigated the four hypotheses of the moderation effects for the most frequent listing types in London, namely entire home and private room. In Models 7 and 8, we tested the moderating role of host reputation; in Models 9 and 10, the role of host responsiveness; in Models 11 and 12, the role of host experience; while in Models 13 and 14, the role of host performance. For the first type of listing (i.e., entire home), we found a moderating effect of host responsiveness (Model 9) and host experience (Model 11), while for the second listing type (i.e., private room), these variables did not have a significant moderating effect in the relationship between cancelations and occupancy rate. However, host reputation played a significant moderating influence with private room listings (Model 8). Finally, Models 13 and 14 confirm the absence of moderating effects of host performance in all listing types.

In Table V, we tested the four hypotheses with apartments, houses, and townhouses. In the regression models 15, 16, and 17, we assess the role of host reputation; in the regression models 18, 19, and 20, we assess the role of host responsiveness; in the regression models 20, 21, and 22, the role of host experience; and in the regression models 24, 25, and 26, the role of host performance.

For the first property type, namely apartment, we found a moderating effect of host responsiveness (Model 18) and host experience (Model 21). For houses, the moderating effect is verified for host reputation (Model 16), while for townhouse, the moderating effect is verified for host reputation (Model 17), host responsiveness (Model 20), and host experience (Model 23). In line with the previous findings (i.e., Hypothesis 5), host performance did not play a significant moderating effect for different property types. Overall, these results highlight the moderating role of property type. Thus, we can conclude that property types moderate, in some cases, the relationship between source credibility signals, host cancelations, and host's occupancy rate.

VI. Discussion and Conclusion

A. *Theoretical Contribution*

This is the first study that focuses on the role of a negative signal, host cancelations, on occupancy rates. The prominent theoretical contribution of this study is that we adopt signaling theory [19], [24] for the first time in the sharing economy context, and we integrate it with the source credibility theory by expanding it. We conceptualize a negative host signal, namely booking cancelations, and host credibility signals, such as host reputation, host experience, host responsiveness, and host performance.

Further, we measured the relationship between cancelation signals and a measure of business performance, i.e., occupancy rate. Subsequently, we assessed whether source credibility signals, i.e., host performance, responsiveness, expertise, and reputation, moderate the influence of cancelation signals on occupancy rates. We argue that these signals reduce the risk embedded in hosts with canceled reservations, contributing to research on risk reduction signals for buyers. These signals are fundamental for consumers because they reduce information asymmetries and uncertainty (e.g., [50], [51], and [54]) in the P2P context. By doing so, we open new avenues for research integrating signaling theory and source credibility theory and contribute to research on the moderating effect of source credibility constructs on consumer behavior (e.g., [29], [35], and [36]), specifically showing the moderating impact of credibility in the relationship between a negative signal and performance in the sharing economy context. We also contribute to research on the role of trust toward a P2P host (e.g., [12]). Previous studies focused on host self-description, host profile picture, linguistic and semantic features in the Airbnb listings, and trust perception [12], [72], [73], [88].

We found that host cancelation(s) is significantly and negatively related to occupancy rates. Thus, the higher the number of cancelations, the lower the intention to book an Airbnb room/flat/home. This result can be explained by the fact that cancelations increase the perceived risk and psychological stress of travel disruptions. It can also be explained by the positivity bias in Airbnb reviews; thus, negative signals are rarer and attention-catching in eWOM settings [89]. Moreover, consumers shy away from reporting negative experiences or comments about Airbnb hosts [6], [41], [55].

Furthermore, cancelations call for additional money, time, and cognitive efforts due to seeking alternative solutions. This result also supports theoretical arguments from the cognitive miser perspective [63], transaction cost theory in the e-commerce environment [64], and risk aversion [65]. The results show that cancelation signals significantly reduce the performance of Airbnb service providers; hence, service providers should reduce, as much as they can, cancelations or, alternatively, refund travelers if they find an agreement for not canceling their reservation on the Airbnb website.

However, we also found that some source credibility signals counteract the negative impact of host cancelations. We found that the host responsiveness lessens the negative impact of cancelations. This result underlines the importance of the interaction speed between hosts and guests in P2P. Due to the higher level of risk and uncertainty, especially in the presence of cancelation signals, the guest needs to be reassured through rapid communications regarding urgent matters like booking confirmation, agreement on arrival time, and the like. We confirm previous studies' results that showed that host responsiveness is a service quality feature [75], indicating host empathy, reliability and trustworthiness, and hospitable attitude (e.g., [32], [56], and [71]–[73]).

Our findings also confirm that the superhost badge (i.e., source reputation) reduces the negative impacts of cancelations. Therefore, the impact from cancelations will be lower if the accommodation is managed by a superhost compared to another host that has not achieved the superhost level. Previous studies proved that hosts who enjoy a superhost badge can use a price premium strategy [13] and guests are willing to submit reviews and higher ratings to hosts who display the superhost badge compared to regular hosts (e.g., [68]). This article affirms the positive role of the superhost badge and shows its economic importance in minimizing host cancelations' (negative) effects on occupancy rates. We can conclude that Airbnb consumers perceive less risk when they book superhost accommodation, even if the host has cancelations on his profile.

We conceptualized host experience in terms of the number of reviews obtained by the host. We found support for the role of host experience as a positive and significant moderator in the relationship between cancelation signals and occupancy rate. Thus, the higher the host experience, the lower is the negative impact of cancelations on the occupancy rate. This result can be explained by the fact that a high number of reviews indicate the host experience as well as his/her willingness to host guests. Signals of host experience also indicate higher host proficiency and familiarity with Airbnb rules and regulations. This result aligns with findings in the hotel industry, where the number of hotel reviews had a significant impact on occupancy rate [43] and eWOM research investigating the influence of popularity signals on purchase intentions and decisions (e.g., [89]).

We conceptualized hosts' performance signal as the average rating score based on the ratings of all the guests who have visited, reviewed, and rated the host accommodation. Surprisingly, our results show that this credibility signal does not play a significant role in moderating the effect of cancelations on the occupancy rate. Accordingly, many studies proved the effect of aggregate ratings on consumers' information adoption and purchase intention (e.g., [80] and [81]), hotel price and sales [84], and hotel occupancy rate [43]. The explanation of the nonsignificant role of performance signals in the Airbnb context is probably due to the skewness of the variable. Accordingly, there is a positivity bias in the Airbnb rating scores, which has been proved in other studies [6], [41], [55]. Our research shows that most ratings are four and five stars; it is plausible that the similarity of rating scores makes it difficult for consumers to discriminate among the different options available.

Finally, we contribute to research on product type as moderator variables in the context of eWOM of accommodation (e.g., [28]). For instance, previous studies found that product type moderates (i.e., hotel size) the impact of extreme rating on review helpfulness [28], while other studies recommended considering the importance of the hotel category or hotel type when studying the predictors of rating scores (e.g., [89] and [90]). In this article, we found that Airbnb property type moderates, in some cases, the relationship between the moderators and cancelations and occupancy rate.

B. Managerial Implications

This study has important managerial implications for Airbnb hosts or other P2P operators. First, our study highlights how cancelations hurt hosts' occupancy rates. This result suggests that Airbnb hosts should avoid, as much as they can, canceling a reservation. Cancelations have detrimental impacts on their occupancy rate in the future.

Furthermore, we have also analyzed the role that different host reputation signals play in lessening the negative effects of cancelations on the hosts' occupancy rate. In the Airbnb context, host signals are provided to reduce the various types of risks that buyers (Airbnb guests) incur when they plan to book a room through this platform and increase the trust toward the Airbnb host.

Moreover, the findings provide the hosts with instructions for presenting themselves effectively and further help earn guests' trust. According to the antecedents influencing guests' perceived trust, the service platforms can focus on building a better trust evaluation system. Besides the reputation system, the response behavior can reflect the host hospitality, which can further influence perceived trust. Therefore, more signals about the host responsiveness could be provided to increase trust on P2P platforms.

C. Limitations and Future Research

Like all studies, our article is not exempt from limitations. First, we focused on London, which, although it is the most important tourism destination in Europe, is not the only one. Therefore, future research could focus on other popular tourism destinations beyond Europe to improve the generalizability of the findings.

Furthermore, research has shown that the eWOM behavior is affected by culture [91]. Hence, scholars could adopt Hofstede's culture value framework and, using surveys and structural equation modeling, compare the influence of cancelations on the intention to book an Airbnb accommodation between high-risk versus low-risk aversion countries to have a cross-cultural validation. Future research could focus on continents where risk aversion is high, for example, China, and compare the impact of cancelations with low-risk aversion countries such as the US. In this context, it would be interesting to analyze perceptual measures to assess whether the host credibility signals moderate the relationships hypothesized in our study.

Future research could also measure the moderation of factors related to the message in the reviews left by Airbnb guests. For instance, latent semantic analytic techniques could be used, as in other studies on hotel accommodations [64], to identify the specific service attributes that make guests satisfied with host listings.

Furthermore, future research could focus on other credibility signals that are, for example, related to the listing. For example, scholars could measure the role of listings' description length, accommodation pictures, listing attributes, and ancillary services (e.g., parking, private bathroom, and so on) as potential moderators of the effect of cancelations on occupancy rate.

Finally, this study adopted data collected prior to the COVID-19 crisis. Although we believe that the theoretical implications of this study are relevant in a post-COVID-19 world, it is probably more likely to expect that negative signals like cancelations might have a stronger impact on host occupancy rates due to the inherent uncertainty connected with choosing a P2P accommodation during and post-COVID-19 crisis. Hence, the magnitude of the impact of cancelations might be higher during the COVID-19 pandemic emergency.

APPENDIX I
DESCRIPTIVES OF THE SAMPLE

TABLE VI
NUMBER AND PERCENTAGE OF LISTINGS BY PROPERTY TYPE

Property type	Number of listings	Percentage of listings
Apartment	4,499	64%
House	1,408	20%
Townhouse	489	7%
Others	608	9%
Total	7,004	100%

TABLE VII
NUMBER AND PERCENTAGE OF LISTINGS BY LISTING TYPE

Listing type	Number of listings	Percentage of listings
Entire home	3,610	51.5%
Private room	3,359	48%
Others	35	0.5%
Total	7,004	100%

TABLE VIII
NUMBER AND PERCENTAGE OF LISTINGS BY NEIGHBORHOOD TYPE

Neighboorhood	Number of listings	Percentage of listings
Westminster	686	10%
Hackney	616	9%
Tower Hamlets	588	8%
Lambeth	534	8%
Camden	529	7%
Others	5051	58%
Total	7,004	100%

TABLE IX
NUMBER AND PERCENTAGE OF REVIEWS BY PROPERTY TYPE

Property type	Number of reviews	Percentage of reviews
Apartment	25,152	60%
House	8,675	22%
Townhouse	3,552	8%
Others	4,231	10%
Total	41,610	100%

TABLE X
NUMBER AND PERCENTAGE OF REVIEWS BY LISTING TYPE

Listing type	**Number of reviews**	**Percentage of reviews**
Private room	26,638	64%
Entire home	14,652	35%
Others	320	1%
Total	41,610	100%

TABLE XI
NUMBER AND PERCENTAGE OF REVIEWS BY NEIGHBORHOOD TYPE

Neighboorhood type	Number of reviews	Percentage of reviews
Westminster	4,846	12%
Lambeth	3,627	9%
Tower Hamlets	3,486	8%
Camden	3,215	8%
Islington	2,937	7%
Others	23,499	56%
Total	41,610	100%

TABLE XII
NUMBER OF REVIEWS AND ACTIVE LISTINGS BY MONTHS

Month	Number of reviews	Number of listings
January	2,435	1,695
February	2,303	1,483
March	2,701	1,717
April	3,235	2,082
May	3,660	2,303
June	4,115	2,449
July	4,819	2,868
August	3,693	2,367
September	4,005	2,404
October	4,153	1,463
November	3,399	1,988
December	3,093	1,952

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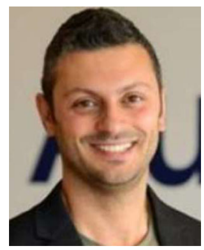

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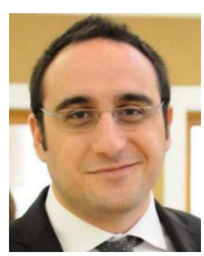

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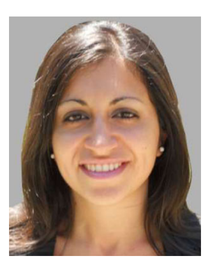

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