

Negative signals on Peer-to-Peer platforms: The impact of cancellations on host performance across different property types

*Original*

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1 **Negative signals on Peer-to-Peer platforms: The impact of host cancellations on**  
2 **occupancy rate across different property types**

3

4 **Abstract**

5 Scholars investigated the factors enhancing Airbnb hosts' performance; however, less  
6 research focused on negative signals, such as host cancellation messages. Cancellations are a  
7 signal that conspicuously reveals the number of times a host has canceled a pre-existing  
8 reservation. Drawing upon signaling theory and product involvement, we argue that  
9 cancellation signals have a negative impact on host occupancy, but this impact is moderated  
10 by the level of involvement associated with the accommodation type (i.e., private room,  
11 shared room, entire apartment). The study used a dataset of 31,778 reviews of 6,384 Airbnb  
12 listings. The results show that accommodation type moderates the relationship, that is, the  
13 impact of cancellations is stronger for higher involvement accommodations (entire apartment)  
14 *versus* low involvement ones (shared rooms). This study advances the literature on negative  
15 signals and helps P2P managers understand the impact of cancellations on their revenues.

16 **Keywords:** Airbnb host; signaling theory; negative signal; cancellation rate; accommodation  
17 type; occupancy rate.

18

19 **Introduction**

20 Peer-To-Peer (P2P) short-term accommodation rental platforms like Airbnb provide  
21 various signals to reduce consumer risks and facilitate the assessment of the reputation and  
22 reliability of hosts (Mauri et al., 2018; Abrate & Viglia, 2019). These signals are used to  
23 communicate the quality, professionalism, and reliability of hosts (e.g., Ert et al., 2016; Dogru

24 et al., 2020). Rating score, the super host badge, profile photos, the volume of reviews, multi-  
25 listings, response rate, responsiveness, years of experience, and identity verification are  
26 signals that impact host performance (e.g., Ert et al., 2016; Xie and Mao, 2017; Wu et al.,  
27 2017; Tussyadiah and Park, 2018; Mauri et al., 2018; Abrate and Viglia, 2019; Dogru et al.,  
28 2020; Xie, Heo, and Mao, 2021).

29         However, less research has focused on negative signals generated by the host and that  
30 communicate the level of unreliability of a host, namely the automated cancellation message  
31 generated by Airbnb each time a host cancels a pre-existing reservation. Cancellations  
32 represent a negative (conspicuous) signal showing the number of times a host cancelled a  
33 reservation. This negative signal is supposedly used by guests to assess the hosts' reliability  
34 and may impact booking decisions.

35         Drawing upon signaling theory (Spence, 1978), negativity bias (Herr, Kardes, & Kim,  
36 1991), and product involvement (Quester & Lim, 2003), we assess the impact of cancellation  
37 rate on host performance considering the moderation of involvement of the product being  
38 booked (Quester & Lim, 2003). The study advances these theories and shows their application  
39 in the P2P context, helping Airbnb hosts to evaluate the impact of cancellation on their  
40 occupancy rate.

41

## 42 **Signaling Theory and Host Cancellations**

43         Signaling theory indicates the use of various signals to conspicuously communicate  
44 the quality of products or services that would be otherwise difficult to evaluate by consumers  
45 due to the presence of information asymmetries (Spence, 1978). Service quality signals are  
46 used to reduce the information asymmetry present between service providers and customers  
47 interested in the purchase of services (Kirmani & Rao, 2000).

48 We divide signals into *user-generated signals*, such as review valence and rating  
49 score, or *host-generated signals*, such as the listing description, the price, and the number of  
50 cancellations. The former signals generally convey positive meanings, and they have received  
51 attention from tourism scholars (e.g., Liang et al., 2017). However, negative signals in P2P  
52 contexts have received scant research attention. In this context, negative signals could be  
53 negative reviews and rating scores left by guests; however, scholars revealed that Airbnb  
54 customers are less likely to leave negative reviews about peer-to-peer hosts because the home  
55 experience shapes consumers' relationships (Osman, D'Acunto, & Johns, 2019) and creates  
56 empathy (Pera et al., 2019). Negative signals can also be generated by the host. For instance,  
57 the cancellation rate is a signal that depends on the number of times a host has unilaterally  
58 canceled a reservation. The cancellation rate is a negative signal automatically generated by  
59 Airbnb when the host cancels a booking, and it is visible in the review profile of the host. The  
60 cancellation can signal the level of unreliability of an Airbnb host. The cancellation rate can  
61 be considered a form of host-generated negative eWOM.

62 The impact of negative signals on Airbnb host performance has received limited  
63 research attention. Drawing upon negativity bias theory (Herr et al., 1991), we argue that a  
64 negative signal like cancellation rate has a strong impact on consumer behavior due to the  
65 negativity bias, that is, the consumers' tendency to evaluate negative information as more  
66 salient, diagnostic, useful than positive information (Wu, 2013). The impact can be  
67 particularly important in the context of Airbnb, which is characterized by high levels of risk  
68 compared to traditional accommodations (Wu, Ma, & Xie, 2017).

69 In this study, we also assume that the impact of cancellation signals on host  
70 performance depends on product involvement. The level of involvement with a product  
71 purchase depends on the hedonic value and perceived importance of the product, but also on

72 the level of psychological, time, financial, social, and physical risks (e.g., Quester & Lim,  
73 2003). Airbnb accommodation types have varying levels of involvement. Entire apartments  
74 are riskier because they are more expensive (economic risk). They are also more complex  
75 because of the higher number of features to consider and assess compared to a shared or  
76 private room in an apartment. Guests of shared rooms or apartments often consider the  
77 accommodation a foothold, and they only assess basic services before booking them.  
78 Furthermore, booking an entire apartment also indicates the higher importance of the trip due  
79 to the potential involvement of other people staying at the accommodation (social risk).  
80 Hence, we formulate the following hypothesis:

81 **H1:** Cancellation rate has a strong impact on host occupancy; however, this impact is  
82 moderated by the type of accommodation, that is, cancellation rate will have a stronger impact  
83 for higher involvement accommodation (entire-apartment) compared to lower involvement  
84 ones (shared-private rooms).

85

## 86 **Methodology**

### 87 *Research setting and measures*

88 London is our research setting since it is among the Top 10 tourism destinations. Our  
89 sample is based on 31,778 reviews of 6,384 Airbnb listings in London in 2019 from AirDNA.

90 The dependent variable in our models is the occupancy rate of each listing monthly.  
91 The occupancy rate (provided by AirDNA) was computed as follows:  $\text{Occupancy rate} = \frac{\text{Total Booked Days}}{\text{Total Booked Days} + \text{Total Available Days}}$ . Various control variables were  
92 added to the model (see Table 1) (e.g., Xie and Mao, 2017; Abrate and Viglia, 2019). The list  
93 of dummy variables refers to the month and property type. The independent variable, the  
94 cancellation rate, was measured as the percentage of cancelled reservations (Table 1).  
95

96 **Table 1.** Variables and operationalization

97

| Variable                       | Operationalization   |
|--------------------------------|--|
| <i>Dependent variable</i>      |  |
| Occupancy Rate*                | Total Booked Days/(Total Booked Days+Total Available Days)                                   |
| <i>Independent variables</i>   |  |
| Cancellation Rate**            | Percentage of cancelled reservations   |
| <i>Moderator variables</i>     |  |
| Property Type                  | List of dummy variables of the property type (Apartment, private room, shared room)          |
| <i>Control variables</i>       |  |
| Host Reputation**              | Dummy variable equal to 1 if the host is a superhost, 0 otherwise                            |
| Host Responsiveness**          | Log percentage of new inquiries and reservation requests a host responded to within 24 hours |
| Host Experience**              | Log of the total number of reviews received by the host                                      |
| Number of Photos**             | Log of the number of photos  |
| Flexible cancellation policy** | Dummy variable equal to 1 if the cancellation policy is flexible, 0 otherwise                |
| Neighborhood type              | List of dummy variables of the neighborhoods   |
| Month                          | List of dummy variables of the month   |

98 Note: \*: data have a monthly base; \*\*: data have a yearly base.

99

100 **Results**

101 The descriptive statistics are reported in Table 2 below. They show that occupancy  
 102 rate is equal to 70.1% while the cancellation rate is higher for entire apartments compared to  
 103 shared or private rooms. As suggested by Sainaghi (2020), we included in the models control  
 104 variables related to host attributes as host reputation, host responsiveness, host experience,  
 105 number of photos posted and the flexible cancellation policy, as well as those related to  
 106 location of the listing as the neighborhood where the listing is located.

107 **Table 2.** Descriptive Statistics

108

| Variable   | Mean   | Standard deviation | Minimum | Maximum |
|--|--------|--------------------|---------|---------|
| <i>Dependent variable</i>                          |        |                    |         |         |
| <i>Occupancy rate</i>                              | 0.701  | 0.287              | 0       | 1       |
| <i>Independent variables</i>                       |        |                    |         |         |
| <i>Cancellation rate (all the sample)</i>          | 0.042  | 0.194              | 0       | 1       |
| <i>Cancellation rate (entire apartments)</i>       | 0.053  | 0.216              | 0       | 1       |
| <i>Cancellation rate (shared or private rooms)</i> | 0.025  | 0.149              | 0       | 1       |
| <i>Moderator variable</i>                          |        |                    |         |         |
| <i>Listing type (entire apartment)</i>             | 0.722  | 0.459              | 0       | 1       |
| <i>Control variables</i>                           |        |                    |         |         |
| <i>Host Reputation</i>                             | 0.420  | 0.493              | 0       | 1       |
| <i>Host responsiveness</i>                         | 96.738 | 10.788             | 0       | 100     |

|                                     |        |        |   |     |
|-------------------------------------|--------|--------|---|-----|
| <i>Host experience</i>              | 1.615  | 1.080  | 1 | 17  |
| <i>Number of photos</i>             | 19.988 | 13.320 | 1 | 200 |
| <i>Flexible cancellation policy</i> | 0.129  | 0.335  | 0 | 1   |
| <i>Neighborhood type</i>            | 20.237 | 9.281  | 1 | 33  |
| <i>Month</i>                        | 6.787  | 3.234  | 1 | 12  |

109

110 We computed the variance inflation factors (VIFs) to exclude any potential  
 111 multicollinearity problems. Since the variables have VIFs well below the suggested threshold  
 112 of 10 (Kleinbaum, Lawrence, Muller, & Nizam, 1998), multicollinearity is not a problem.

113 We then run four longitudinal econometric regression models monthly to test the  
 114 effects of cancellation rate on occupancy rate, including all property types and the three  
 115 subsamples separately (entire apartment, shared room, and private room) (Table 3). In Model  
 116 1, the effect of cancellation rate on occupancy rate is negative and significant. Models 2, 3  
 117 and 4 include, respectively, the three listing types of entire apartments, shared rooms, and  
 118 private rooms. The significant effect of cancellation rate on occupancy rate in Model 2 and  
 119 the non-significant effect in Model 3 and Model 4 support the hypothesis that the cancellation  
 120 rate has a stronger and more significant impact for higher involvement accommodations  
 121 (entire apartment) compared to lower involvement ones (shared rooms and private rooms).

122 **Table 3.** Longitudinal regression models

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| <i>Independent variables</i> | <i>Dependent variable</i> |                         |                    |
|------------------------------|---------------------------|-------------------------|--------------------|
|                              | <i>Occupancy rate</i>     |                         |                    |
|                              | <i>M1</i>                 | <i>M2</i>               | <i>M3</i>          |
| <i>Property Type</i>         | <i>All</i>                | <i>Entire apartment</i> | <i>Shared room</i> |
| <i>Direct effects</i>        |                           |                         |                    |
| Cancellation Rate            | -0.038*                   | -0.051**                | -0.023             |
|                              | (0.020)                   | (0.023)                 | (0.033)            |
| <i>Control variables</i>     |                           |                         |                    |
| Host Reputation              | 0.026***                  | 0.023*                  | 0.016              |
|                              | (0.008)                   | (0.010)                 | (0.016)            |
| Host Responsiveness          | 0.038***                  | 0.033*                  | 0.066*             |
|                              | (0.014)                   | (0.015)                 | (0.034)            |
| Host Experience              | 0.033***                  | 0.041***                | 0.022*             |
|                              | (0.005)                   | (0.007)                 | (0.008)            |
| Number of photos             | 0.011                     | -0.005                  | 0.046***           |
|                              | (0.007)                   | (0.008)                 | (0.011)            |
| Flexible cancellation policy | -0.034*                   | -0.038*                 | -0.026             |
|                              | (0.014)                   | (0.017)                 | (0.020)            |
| Constant                     | 0.445**                   | 0.264                   | 0.609*             |
|                              | (0.146)                   | (0.188)                 | (0.244)            |
| R-squared overall            | 15.72%                    | 16.81%                  | 12.18%             |
| VIF                          | 1.54                      | 1.79                    | 1.39               |
| <i>Observations</i>          |                           |                         |                    |
| Number of listings           | 3,075                     | 2,221                   | 1,088              |
| Percentage of listings       | 100.00%                   | 72.23%                  | 27.77%             |

133 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  
134 months, type of neighborhood and the property type dummies (in Model 1) are omitted.

135

## 136 Discussion and Theoretical Contribution

137 This study advances the literature on home sharing by investigating a negative host  
138 signal, the booking *cancellation signal*. Negative signals generated by hosts have received  
139 scant research attention, whereas previous studies on positive signals (e.g., superhost, rating  
140 score, profile picture, multi-listing) have proved their effect on host performance metrics (e.g.,  
141 Xie and Mao, 2017). This study has integrated arguments from the negativity bias theory  
142 (Herr et al., 1991; Wu, 2003; Filieri, Raguseo, and Vitari, 2019) and signaling theory (Spence,  
143 1978; Kirmani and Rao, 2000) and applied them to the P2P context, by advancing the  
144 literature on conspicuous negative signals.

145 This study is the first that assesses the negative impact of cancellation rate on host  
146 occupancy, advancing the literature on the effects of negative signals on peer-to-peer  
147 platforms in the home-sharing context. We can conclude that a host that cancels an existing  
148 reservation is perceived as less reliable compared to others who do not cancel any reservation.  
149 Hence, guests are less likely to book an Airbnb accommodation from a host that has cancelled  
150 pre-existing reservations.

151 Furthermore, this study also shows that the impact of cancellation rate is not uniform  
152 across accommodation types, that is, cancellation rate impact is significant for high  
153 involvement products, entire apartments in our study. This result contributes to the literature  
154 that suggests that the impact of negativity bias depends on some conditions that can moderate  
155 its impact, such as the type of product (Filiari et al., 2019; Mudambi and Schuff, 2010). The  
156 study also links to the literature on the role of product type in the P2P context. Consistently,  
157 scholars have shown that travelers are less likely to reserve some types of Airbnb  
158 accommodation (i.e., shared accommodation) for fear of social contact during the Covid-19  
159 pandemic (Dogru et al., 2020; Bresciani et al., 2021). Other scholars revealed that different  
160 Airbnb properties (entire homes, private rooms, or shared rooms) impact lodging  
161 organizations differently (Dogru et al., 2020). Hence, this study stresses the relevance of  
162 accommodation type in evaluating the effects of the determinants of host performance.

163 This result also contributes to the literature on product involvement (Quester & Lim,  
164 2003). Higher cancellation rates are particularly detrimental for high-involvement  
165 accommodation types (entire apartments) compared to low-involvement ones (shared rooms).

166

167 **Managerial implications**

168 This study highlights that hosts of entire apartments should pay particular attention to  
169 cancellation signals because they strongly impact the occupancy rate. Cancellation signals  
170 increase the risk and decrease the confidence in the service provider, reducing the intention to  
171 book. Our recommendation to Airbnb hosts of entire homes is to try to reduce to a minimum  
172 the possibility of canceling an existing reservation. For instance, hosts could eventually ask  
173 for help from neighbors or consider adopting code-based keyless entry door locks.

174

### 175 **Limitations and future research**

176 Future research could include various destinations in other countries other than the UK.  
177 Scholars could assess if and how much cancellation rates moderate the impact of generally  
178 positive user-generated signals in Airbnb, such as review valence and the rating score. Future  
179 research could also consider other negative host-generated signals such as negatively valenced  
180 reviews or negative ratings, the unprofessional description of listings, or the absence of visual  
181 information about key features of a property (i.e., bedroom).

182

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