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HOW MUCH WILL YOU PAY? UNDERSTANDING THE VALUE OF INFORMATION CUES IN THE SHARING ECONOMY

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HOW MUCH WILL YOU PAY? UNDERSTANDING THE VALUE OF INFORMATION CUES IN THE SHARING ECONOMY

Research paper

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Abstract

The advent of peer-to-peer accommodation sharing platforms, like Airbnb, has ushered in a new era in travel worldwide. However, to ensure sustainability in the long term, information asymmetry inherent to such platforms has to be tackled. Currently, accommodation sharing platforms offer a multitude of in-built trust-enhancing cues that may reduce information asymmetry, signal trust and aid potential guests in their decision making. Nevertheless, little is known about the effectiveness of these cues in shaping online consumption behavior. Building on the Signalling Theory, this study explores the effectiveness and monetary value of three groups of trust-enhancing cues commonly deployed by service providers to promote trust in the sharing economy via a discrete choice experiment methodology. Findings from our study not only contribute to extant literature on the effectiveness of trust-enhancing cues, but they also empower platform providers and hosts through novel insights on how the performance of their offerings is evaluated by consumers.

Keywords: Sharing Economy, Trust-Enhancing Signals, Price Premium, Discrete Choice Experiment.

1 Introduction

The advent of the new “sharing economy” has revolutionized consumption habits. Platforms, which facilitate peer-to-peer sharing of housing (e.g., Airbnb, 9flats), cars and drivers (e.g., UBER) and parking places (e.g., ParkatmyHouse), have witnessed stunning growth given that consumers can now enjoy the benefits of possession without the responsibility of ownership. These developments have been particularly transformative for the hospitality industry with platforms, like Airbnb, claiming a major share of a market that is traditionally dominated by commercial establishments. Beyond cost savings for tenants, accommodation sharing affords a level of home-like hospitality that is generally unavailable from such establishments. In turn, accommodation sharing has brought about discernible economic benefits, with Airbnb guests staying longer than those staying in commercial establishments, and also spending 2.1 times more (Airbnb, 2016a).

Despite the optimism surrounding the sharing economy, critics have called into question the risks of this growing phenomenon (Baker, 2014). Detractors of accommodation sharing have often cited issues such as money scams, unsatisfactory hygiene, noise and even harassment (e.g., airbnbhell.com, 2016; sitejabber.com, 2016). Indeed, while commercial establishments are subjected to stringent regulations with regards to their cleanliness and service, private hosts do not have to comply with such stipulations. Coupled with the fact that guests are typically not furnished with the exact identity of the host and the location of the apartment before concluding a transaction, inherent information asymmetries imply that guests must make choices under conditions of uncertainty. Consequently, reducing uncertainty and promoting trust between hosts and guests is critical for any provider operating in the peer-to-peer accommodation sharing space.

Trust is often touted as the invisible ‘currency’ powering the sharing economy as it underlies consumer choices and enables transactions (Botsman, 2012; Edelman and Luca, 2014). Consequently, platforms, like Airbnb, have dedicated prominent sections on their sites to draw attention to the importance of trust for their consumer community and to offer commensurable remedies whenever this trust is broken (see Airbnb, 2016b). For example, a USD \$1 million insurance is offered by Airbnb to protect hosts from unexpected damage to their property. For potential guests, Airbnb contains *trust-enhancing cues* (or *signals*) to aid them in making informed decisions. Feedback systems featuring opinionated reviews, star ratings and peer references translates into insightful signals that can be harnessed by potential guests to compare offerings (Chatterjee, 2001; McKnight et al., 2002a; 2002b).

Prior research has introduced *cue-based trust* as a concept that contrasts with experience-based trust (Wang et al, 2004). While certain cue have been discovered to be critical in enhancing trust which in turn positively influences behavioural outcomes in retail (Wang et al, 2004) or peer-to-peer sharing networks (Zervas et al., 2015; Möhlmann, 2016), little is known about their individual effectiveness. Amid a diversity of cues, which are the ones determining guests’ final decision and how do they differ in their relative impact? Are guests ready to pay more for an accommodation if a specific cue is provided, and if so, by how much? In other words, what is the price premium for trust on these platforms? To answer these questions, we build on the Signalling Theory and employ a Discrete Choice Experiment methodology to explore the effects of three groups of trust-enhancing signals in the peer-to-peer accommodation sharing context. In doing so, we are able to differentiate among distinct influences produced by discrete trust-enhancing cues and derive a monetary value for each of these cues as evaluated by consumers.

From a theoretical standpoint, our study contributes to extant literature on the effectiveness of trust-enhancing cues in online settings (Wang et al, 2004; Wells et al., 2011; Zervas et al.; 2015; Möhlmann, 2016). To the best of our knowledge, this study is the first to ascertain monetary valuation for distinguishable levels of trust-enhancing cues. In addition, our empirical findings may enrich existing research on how consumers interact with trust-enhancing cues in the context of the sharing economy. On the practical front, platform providers and hosts may leverage on the results of our study to infer cues for which they should emphasize when designing their offerings.

2 Theoretical Background

2.1 Understanding the Need for Trust-Enhancing Signals

Information asymmetry is intrinsic to economic transactions because sellers typically possess more information about the quality of their offerings than buyers (Ba and Pavlou, 2002). Due to these imbalances, sellers are enticed to engage in opportunistic behaviour (Williamson, 1975) such as incomplete disclosure, “*taking shortcuts, breaking promises, masking inadequate or poor quality work*” (Provan and Skinner, 1989, p. 203). However, since markets vary (i.e., both high- and low-quality goods are traded), not all agents behave opportunistically (Knorrninga, 1994). This translates into an acute problem of distinguishing honest agents from their opportunistic counterparts. To tackle this, buyers may attempt to assess the trustworthiness of the potential partner as a means of resolving the adverse selection problem (Williamson, 1975; Akerlof, 1970). Defined as perceptions formed by consumers on the basis of “*cues received from an initial encounter [and encapsulating their beliefs about the extent to which their] vulnerabilities will not be exploited*” (Wang et al., 2004, p. 54), trust emerges as a focal concept facilitating decision-making and transactions online (Ba and Pavlou, 2002).

Since the ability to assess the trustworthiness of the other party online is often limited, consumers are likely to resort to peripheral cues to guide them in their cognitive assessment process (Chaiken, 1980). This suggests a paramount role of trust-enhancing cues under conditions of uncertainty (Petty and Cacioppo, 2012). Signalling Theory thus emerges as an appropriate theoretical lens for explaining how information asymmetries can be mitigated via the provision of pertinent trust-enhancing cues (Spence, 1973; Akerlof, 1970). Specifically, effective cues – those that are costly, observable and verifiable – are found to be invaluable in assisting outsiders to tell apart a high-quality offering from a low-quality one (Connelly et al., 2011; Li et al., 2009). Having received a signal, a recipient is expected to adjust his/her attitude and behaviour accordingly, which can take the form of increased willingness to transact and pay a price premium for an offering (Coff, 2002).

2.2 Trust-Enhancing Signals in the Accommodation Sharing Context

While popular accommodation sharing platforms, like Airbnb, share commonalities with traditional e-commerce platforms, they also exhibit unique contextual characteristics that may alter the nature of uncertainties inherent to sharing arrangements. First, the sharing economy does not involve the transfer of ownership, but rather, accentuates the joint consumption of shared resource. This implies greater intensity of interaction between parties over the consumption duration (Bardhi and Eckhardt, 2012). Second, sharing platforms focus on the provision of services, rather than goods (Knote and Blohm, 2016). Here, unique characteristics of services (e.g., intangibility, heterogeneity, inseparability of production and consumption) have far-reaching implications for quality judgements. Third, the quality of shared services is largely unregulated (Sundararajan, 2014), which may fuel consumer uncertainty. Acknowledging these peculiarities, platform providers, like Airbnb, introduce an elaborate set of verifiable trust-enhancing cues that supposedly reduce uncertainty for guests. The introduction of such cues also supplies hosts with a workable framework for reducing guest uncertainty towards their offerings. Broadly, trust-enhancing cues on accommodation sharing platforms can be clustered into *three* separate groups: (1) *feedback system*; (2) cues derived from a *social graph* articulated by an online user, and; (3) validated linkages between online and offline identities of the host - *offline verifications and telepresence* (Table 1).

The effectiveness of *feedback systems* (1) is rooted in their ability to restrain undesirable behaviour by imposing costs on opportunistic vendors in terms of future lost profits (Ba and Pavlou 2002). Cues, such as reviews, recommendations and star ratings have been routinely associated with trust and sales in the e-commerce context (e.g., Zervas et al., 2016; Chen et al., 2004). For example, Ba and Pavlou (2002) note that positive ratings have the potential to mitigate information asymmetries, culminating

in a price premium for sellers. The impact of these cues is especially pronounced in the hospitality industry (Ye et al., 2011; Liu, 2006). For example, 35% of guests switch their choice of hotels after reading online reviews (World Travel Market Industry Report, 2010). Many sharing platforms have thus incorporated feedback elements. Airbnb encourages hosts and guests to rate the other party upon the completion of the transaction (Edelman and Luca, 2014). Yet, the effectiveness of these mechanisms has been questioned in the context of the sharing economy (Zervas et al., 2015). The reasons are three-fold. First, stakeholders accuse Airbnb of removing negative reviews, thereby eroding the ability of potential guests to arrive at an objective opinion (e.g. Schaal 2012). Second, until recently, guests and hosts could see mutual reviews beforehand, breeding fears of retaliation and suppressing honest opinions (e.g., Weber, 2014; The BnB Life, 2013). Third, individuals appear reluctant to criticize others (e.g. hosts) online even if their experience was unsatisfactory (e.g., Zervas et al., 2015). Together, these flaws may undermine the credibility of the feedback system, calling for a need to revisit its effectiveness in the context of sharing economy.

P2P Platform	Trust-Enhancing Cues			Social Graph			Offline Verification and Telepresence							
	Reviews	Ratings	References	Facebook	LinkedIn	Google+	Photo of a host	Verified ID	Verified photo of apartment	About me	Response rate	Response time	Calendar update	Membership duration
<i>Paid accommodation sharing services</i>														
Airbnb	x	x	x	x	x	x	x	phone, e-mail, offline ID	x	x	x	x		x
Homeaway	x	x					x	phone open		x	x	x	x	x
VRBO	x	x						phone open, e-mail			x	x	x	x
Flipkey	x	x					x	phone open		x	x	x	x	
Roomorama	x	x					x	certified host		x	x	x	x	x
Wimdu	x	x					x			x	x	x	x	
9flats	x	x		inner SNS			x	verified host	x	x	x	x		
HouseTrip	x	x					x				x	x		x
Homestay	x	x					x			x	x	x		x

Table 1. Common trust-enhancing cues for paid accommodation sharing platforms.

Cues based on online *social graph* (2) represent another group of signals with trust-enhancing properties. In the sharing context, both external (e.g., Facebook for Airbnb) and internal social networks can be leveraged in unison. For example, social networks disclosed online can be employed to establish a connection – often in the form of *common ground* – between a guest, a host, and a specific offering. The effectiveness of this approach can be traced back to the principle of homophily, which holds that similarity between partners, in terms of demographics or viewpoints, promotes trusting relationships (Ibarra, 1993; McPherson et al., 2001). For instance, Airbnb not only allows users to search for accommodations offered by their Facebook friends, but it also notifies a user when a friend has reviewed an offering. Potential guests are also informed when the host has attended the same university. Furthermore, measures related to individual social graph structure can be utilized to verify of his or her online identity and draw further inferences (Staiano et al., 2012; Airbnb, 2016b). For example, Airbnb communicates how many Facebook friends a host has. Nonetheless, prior research has remained divided on the effectiveness of this trust-enhancing cue (Tong et al., 2008). On one hand, a high number

of friends on a Social Networking Site not only signals that a profile is unlikely to be fabricated, but it also has been associated with positive perceptions of the profiler such as popularity (Utz, 2010), pleasantness, confidence and heterosexual appeal (Kleck et al., 2007). On the other hand, past studies have reported that individuals with very large networks were deemed to be less socially attractive (Tong et al., 2008), promiscuous and hence, not trustworthy (Westlake, 2008; Donath and Boyd, 2004). While there is only a limited body of empirical research that yields insight into the effectiveness of trust-enhancing cues grounded in social graph, the increasing reliance on such cues in the sharing context calls for a better appreciation of their effectiveness.

Finally, online buyers may question the existence of the other party or the credibility of its reputation offline. This highlights the necessity for (3) “*offline verifications and telepresence*” cues. Looking for ways to deal with fraudulent agents, many sharing platforms establish their own in-house verification services. For example, Airbnb offers to authenticate the identification documents of its users. Such authentication could signal that the other party is real and its reputation history has not been distorted (e.g., by simply changing an e-mail address) (Ba, et al. 2003). Further, hosts may apply to Airbnb to validate their apartment photos to ensure higher credibility (Airbnb, 2016c). Though these signals cooperate to bridge offline and online presence of market participants, their effectiveness in the sharing context is unclear. Prior research also does not yield a unified picture: while some studies revealed a positive impact of trust-enhancing seals granted by an independent third party (Xu et al., 2012; Yang et al., 2006), others find no evidence for these effects (e.g., Hui et al., 2007; McKnight et al., 2004). This in turn calls for better understanding of the effectiveness of such cues for the sharing context. Figure 1 presents the conceptual framework of our study.

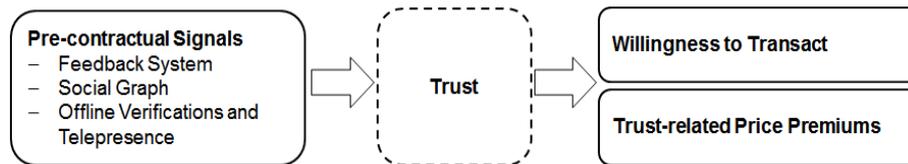


Figure 1. Conceptual framework for the study.

3 Methodology

To derive the value of discrete trust-enhancing cues in accommodation sharing settings, a Discrete Choice Experiment (DCE) was conducted. The DCE approach is founded on a combination of two elements: (1) *discrete choice analysis* to model preferences, and; (2) *stated preference methods* to gather the required data for eliciting these preferences (Viney et al., 2002; Kjær, 2005; Street and Burgess, 2007). *Stated preference methods* allow consumer preferences to be specified in hypothetical, but ‘close to the truth’ scenarios, thereby helping to tease apart the influence exerted by discrete attributes in the choices made by respondents and their valuation of these attributes. This is especially attractive when real choices are difficult to observe. We thus favour the DCE approach over other conjoint techniques that are purely mathematical and are criticized for being inconsistent with a long-standing economic demand theory (Louviere et al., 2010). Underlying DCE, *discrete choice analysis* is rooted in the Random Utility Theory (RUT) (e.g., Manski, 1977; McFadden, 1974), which considers a rational individual i who makes choices between a number of J alternatives in a consistent manner and in accordance with the utility maximization principle. Grounded in the assumption that a researcher lacks information about the true utility function of i , RUT differentiates between the observable systematic component V_{ij} and a random component ε_{ij} that incorporates all unobservable factors of consumer’s choice:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (1).$$

Hence, the probability that a specific alternative j is chosen can be estimated as:

$$\begin{aligned} p_i(j/J) &= \text{Prob}(U_{ij} > U_{ik}) = \text{Prob}[(V_{ij} + \varepsilon_{ij}) > (V_{ik} + \varepsilon_{ik})] = \\ &= \text{Prob}[(V_{ij} - V_{ik}) > (\varepsilon_{ij} - \varepsilon_{ik})] \forall j \neq k, k \in J \end{aligned} \quad (2).$$

Additionally, consistent with Lancaster's (1966) economic theory of value, DCE treats goods as a bundle of attributes since "*these characteristics give rise to utility, not goods themselves, on which the consumer's preferences are exercised*" (p. 134). Therefore, the observable utility of a good (specific alternative j) is the sum of the utilities of its individual attributes:

$$V_{ij} = \beta x_{ij} = \sum_m \beta_m x_{mji} \rightarrow U_{ij} = \beta x_{ij} + \varepsilon_{ij} \quad (3),$$

where x_{ij} is a vector of m attributes related to the alternative j , and β represents vector parameters of corresponding attributes. The output of the model is the estimated discrepancy in utilities among alternatives caused by difference in utilities for each attribute. Since probabilities and estimated utility scores are numeric values, it is possible to estimate a marginal rate of substitution (MRS), which can be interpreted as consumers' willingness-to-pay (WTP) for a change in the level of an attribute assuming that the vector of attributes includes costs (Kjær, 2005). Taken together, by analysing the choices of respondents across selected sets of alternatives, DCE enables the identification of the importance and monetary value of considered attributes, thereby rendering it a suitable tool for our study.

3.1 Model Specification

The DCE approach involves three key stages: (1) model specification; (2) experimental design, and; (3) questionnaire development (Rose and Bliemer, 2008; Johnson et al., 2013). To determine the impact of discrete cues on users' willingness to engage in a transaction, a hypothetical scenario of choosing an accommodation in Milan via a fictional peer-to-peer platform 'privateflats.com' was designed (to avoid branding effects of existing market players). In the first stage of (1) model specification, relevant attributes and their levels were determined. There is growing consensus that selected attributes should reflect essential characteristics of the focal product (Abihiro et al., 2014). In light of our preceding discussion on the widespread adoption and theoretical relevance of signals related to the *feedback system*, *social graph* as well as *offline verifications and telepresence* (see Table 1 and Section 2), we opted to explore the effects of five selected cues (attributes), which we deem to be representative of these three groups of signals. Additionally, since shared rentals are typically associated with *monetary costs*, this factor was included as an attribute (*f*) *price* in our experimental set-up. To ensure that levels of the chosen attributes are "*plausible and capable of being traded*" (Coast and Horrocks, 2007, p. 25), we drew on the findings from a pilot study, in which characteristics of 200 *private room* listings offered for rent in Milan on Airbnb were inspected. The sample selection for this pilot exploration was not intended to be comprehensive but rather embraced an exploratory objective. The following search criteria were applied for the sample selection: *size*: 1 bedroom, 1 bathroom, 1 bed; *neighbourhood*: whole city; *dates of the trip*: 27.11.2014 – 28.11.2014 and *price*: at least ≈ 11 Euro (for details see Abramova et al. 2015). Subsequently, content analysis was performed on the elicited listings to collect data on attributes (e.g., price and number of Facebook friends) that we can reference when deciding on attribute levels.

Summarized in Table 2, our proposed model specification addresses the crucial trade-off between the trustworthiness of an offering and its price. In our model, the (a) *number of positive reviews* per listing was employed to represent a '*feedback system*' group of signals. Several reasons guided this choice. First, in the e-commerce context the number of online reviews has been identified as a major driver of consumer purchasing decisions (Chen et al., 2004; Godes and Mayzlin, 2004). Second, our choice to

focus on the positive type of feedback was dictated by the overwhelming prevalence of such reviews on the accommodation sharing platforms (Zervas et al., 2015). This was also supported by the findings from our pilot study, in which 88% of all inspected reviews ($N = 4467$) contained only positive evaluations.

Attributes: Descriptive Text Displayed in the Experiment		Attribute Levels
Feedback System	(a) Number of Positive Reviews¹: To facilitate the assessment of the trustworthiness of the offer, the reviews for the corresponding accommodation from other guests are published. In reality, these reviews are almost always positive, for this reason only their number is presented.	<ol style="list-style-type: none"> 1) No reviews available so far 2) 1 positive review 3) 5 positive reviews 4) 15 positive reviews
Social Graph	(b) Common Ground with the Host: Hosts and guests can specify their (former) university and other information about themselves when registering. If there are similarities between the host and the guest, they are displayed. Otherwise, no information is provided.	<ol style="list-style-type: none"> 1) No similarities with the host could be established (<i>in this case no information was shown</i>) 2) Host studied at the same university as the guest (respondent)
	(c) Number of Facebook friends: A host is given the opportunity to link his platform account with his Facebook account. This way one can see the number of Facebook friends the host has. It is also possible that the host does not specify a link to his Facebook account.	<ol style="list-style-type: none"> 1) Account of the host has not been linked with Facebook (<i>in this case no information was shown</i>) 2) 75 Facebook friends 3) 200 Facebook friends 4) 743 Facebook friends
Offline Verifications and Telepresence	(d) Verified Personal ID: This online platform provides hosts with an opportunity to verify their personal identity card. This guarantees that the host is a real person. This verification is then displayed on the profile of the host. Otherwise, no information is provided.	<ol style="list-style-type: none"> 1) Verification has not been undertaken (<i>in this case no information was shown</i>) 2) Verified personal ID
	(e) Verified Apartment Photo: This online platform provides hosts with an opportunity for the photos of their apartment to be taken by an accredited photographer. This guarantees that the presented photos correspond to the reality. This verification is then displayed on the profile of the host. Otherwise, no information is provided.	<ol style="list-style-type: none"> 1) Verification has not been undertaken (<i>in this case no information was shown</i>) 2) Verified apartment photo
Monetary Cost	(f) Price per Night: Respondents were also instructed that the suggested offerings may also differ in terms of pricing.	<ol style="list-style-type: none"> 1) € 35 2) € 45 3) € 55 4) € 65

Table 2. Operationalization of variables in our Discrete Choice Experiment.

Selection of the specific levels for this attribute was guided by theoretical and practical interest, as well as the results of our pilot study. This is because the number of reviews per room fluctuate vastly in our data sample with an average of 22.3 and a median of 10 reviews. Furthermore, of particular interest is the likelihood of staying with a host who has not been reviewed yet or has only one review (5% of listings in the pilot study). Four levels of reviews were thus included: 0, 1, 5, and 15 positive reviews (see Figure 2 and Table 2).

¹ When faced with a complex decision-making process, consumers were shown to rely on easy-to-access and easy-to-process online information (Sparks and Browning 2010). Hence, only the *number of positive reviews* was explicitly shown to the respondents in our experiment, while the text in the review area was shadowed to avoid cognitive overload.

Following our theoretical exploration (see Section 2), (b) the presence of *common ground* between a potential guest and a host was deemed to be representative of the ‘*social graph*’ group of cues. The significance of *common ground* is corroborated by the qualitative study of Finley (2013), who revealed that the presence of a social connection has a favourable impact on trust in an Airbnb host. Because students and university graduates form the targeted sample for our study, having attended the same university between a host and a guest could be conceived as being indicative of *common ground* since, in most cases, alma mater is “*the source of person’s cultural capital and intimate sense of fraternal kinship*” (Prendergast and Abelmann, 2006, p. 39), which “*validates [individual] belief that [...] values are in sync*” (Murphy, 2014). Two levels of *common ground* were thus included: ‘no common ground established’ or ‘the host studied in the same university’ as the respondent. Additionally, the (c) *number of Facebook friends* of a host was employed as another cue based on *social graph*. In our exploratory study, the number of Facebook contacts of a host was visible in more than half of the listings ($N = 112$), yielding a mean of 734 and median of 525 friends ($SD = 641$). Moreover, a representative survey by Smith (2014) documented a median number of 200 Facebook friends (mean = 338); 39% of adult users are found to have between 1 and 100 ‘friends’ and 15% have more than 500 contacts. Hence, four levels of Facebook friends were included: ‘account has not been linked to Facebook’, 75, 200 and 743 Facebook friends.

Cues related to “*offline verifications and telepresence*” were operationalized by including the availability of: (d) *verified personal ID*, and; (e) *verified apartment photo* as attributes in our experimental design. *Verified personal ID* (d) is intended to clear doubts about the identity of the account holder and his/her past reputation (Ba et al. 2003). In our pilot study, 40% of the hosts have verified their personal ID with Airbnb, suggesting a reasonable interest in this cue. Two levels of this attribute were thus included: ‘verification has not been undertaken’ and ‘personal ID has been “verified”’. Likewise, *verified apartment photos* (e) can be seen as another signal of trustworthiness. This verification with the help of professional photographers serves multiple purposes. First, listings with high-quality images could contribute to an overall positive impression of the platform, which in turn may induce trusting beliefs towards the platform in general (Finley, 2013; Karvonen, 2000). Second, this verification signals the existence and current condition of the accommodation, thereby reducing another layer of uncertainty concerning the offering (Airbnb, 2016c; Finley, 2013). Two levels of this attribute were included: ‘verification has not been undertaken’ and ‘apartment photo has been “verified”’.

Monetary cost is a salient driver of accommodation choice as the rental *price* (f) should fit a guest’s budget. Our exploratory study of private room listings on Airbnb revealed a broad spectrum of prices ranging from €23 to €150 per night with a mean value of €62 (S.D. = €22) and a median value of €58. To assure the realism of the pricing levels for our sample population, we administered another survey on a sample of university students ($N = 167$) to elicit the general WTP and maximum WTP (i.e., upper bound price) they can afford for an overnight accommodation in Milan. Results yielded a mean value of €56 and a median value of €45 for a general WTP; maximum WTP had a mean value of €78 and a median value of €60. We therefore opted for four pricing levels: €35 (one S.D. away from the median derived in the pilot study); €45 (based on the median general WTP from the survey); €55 (based on the median value in the pilot study and the mean general WTP in the survey-based pre-study); €65 (based on the mean value in the pilot study and the median maximum WTP from the survey).

3.2 Experimental Design, Questionnaire Development and Sampling

In the experiment, participants were first familiarized with the accommodation sharing context by exposing them to a fictional storyline: “*Imagine the following situation: You plan a weekend city trip to Milan. Therefore, you are looking for a room to stay (in an apartment). You are ready to share the rest of the apartment with the host. Your best friend has recommended you an online platform called privateflats.com, in which private people offer rooms or even entire apartments for rent (just like on airbnb.com). After an extensive search, you have selected some rooms that match your taste. Below an example of such a room is presented*”. Next, eleven photos of a room were presented, similar to what

potential guests would encounter on Airbnb or 9flats. We then measured participants' *attitude towards the presented room* via the scale of Bhattacharjee and Premkumar, (2004): Participants were asked to specify if "all things considered, renting this room will be a: (ATT_1) bad idea - good idea; (ATT_2) foolish move - wise move; (ATT_3) negative step - positive step" (using a 7-point semantic differential scale). In the second step, participants were instructed about possible disparities in the listings with respect to the select attributes (see Table 2). It was hinted that: "Although all rooms that you have selected are visually similar, it may be that you still feel some uncertainty when it comes to the final decision. To minimize these uncertainties more information is provided to the potential guests regarding the attributes of specific listings. In our study the listings can differ with regard to the following attributes:" Immediately after, the list of attributes, as shown in Column 2 of Table 2, were presented. Specific values corresponding to different attribute levels were not accessible to participants at this point (Column 3 of Table 2). This presentation preceded a graphical illustration of a listing in which all attributes were highlighted for emphasis. In the third step, participants were offered a series of choice sets in a randomized sequence with two listing alternatives per choice (levels of attributes varied) (see Figure 2).

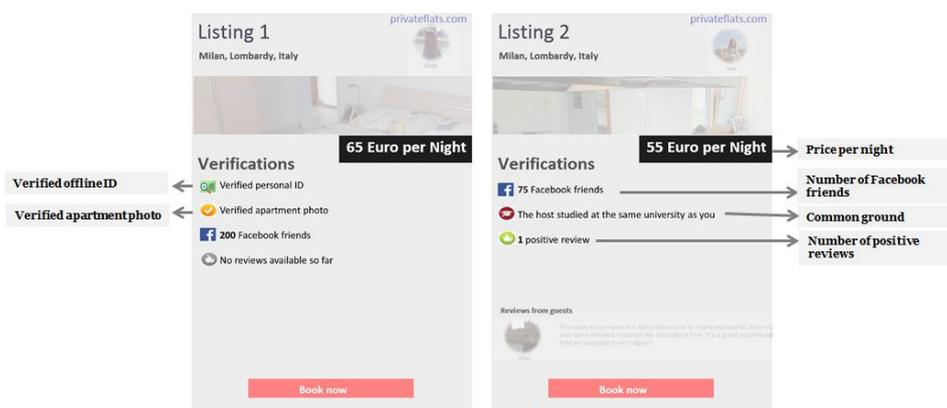


Figure 2. Example of a choice situation in Discrete Choice Experiment².

The 'look and feel' of the listings was similar to the design of popular accommodation sharing platforms with slight variations. In each choice set, respondents were requested to choose one listing alternative that they would rent ('Listing 1' or 'Listing 2'). A 'no choice' option was also included ('I would choose none of these listings') to cover situations where none of presented listings was acceptable for a respondent. The number of choice sets was derived via the D-efficient design. This is because the number of treatments for full-factorial design would be impractical (i.e., $4 \times 4 \times 2 \times 2 \times 2 \times 4 = 512$ possible profiles and $512!/[2!(512-2)!] = 130816$ permutations of two-alternative choice questions). At the same time, D-efficient design represents the most common solution when it comes to the trade-off between statistical efficiency and a pragmatic number of questions to ask (Bliemer and Rose 2010). Computed with the SAS (2015) software, our analysis suggested that the efficient design could be reached with either 16 or 32 distinct choice sets. To minimize the cognitive load for the respondents, we opted for the former option. In the fourth and final step, we solicited participants' demographic information and their previous experience with accommodation sharing platforms.

Participants were recruited via several mailing lists of one German university and by posting on Facebook boards. A lottery of 20 Amazon.de gift cards (€ 10 value each) was offered. 472 usable responses were collected. To check for fatigue and other confounds caused by anonymous responding, a manipulation check was incorporated: the 17th choice card included an alternative that is clearly inferior to the

² Explanations for the attributes were not given across the choice sets and were only utilized for explanatory purposes in the beginning of the survey (see description of Step 2 above).

other. Participants who did not pass this manipulation check or have always chosen the ‘no choice’ option were excluded from further analysis ($N = 22$). We eventually arrived at a final dataset of 450 responses. While discussion about the required sample size for DCE is still ongoing, a common rule of thumb suggests that the minimum size should exceed the following threshold (Orme 2010):

$$N \geq 500 \cdot \frac{L^{\max}}{J \cdot S}, \quad (4)$$

where N is the suggested sample size, L^{\max} is the largest number of levels for any given attribute, J is the number of alternatives and S is the number of choice situations in the design. For our study, this threshold equals $500 \cdot 4 / (2 \cdot 16) = 62.5$, and the actual sample size of $N = 450$ easily surpasses this criterion. In terms of demographics, our sample consists of students (88.4%); 49.6% and 44.9% of participants are aged between 18 and 24, and between 25 and 33 years old respectively. Our sample is somewhat dominated by female participants (68%) and by those who have spent most of their life in Germany (89%). Nearly half of the participants (46.2%) have completed their secondary education, 36.4% have finished their undergraduate studies and 11.3% have graduated with a master degree. 38% of participants have already been guests and 8% have hosted on sharing platforms. Demand for temporary housing was relatively large: last year alone, 30% of respondents needed temporary lodging for 8-14 days in total; 20% for 15-30 days; and 10% for 31-60 days. Respondents also expressed a favourable attitude towards the apartment they were offered as an example in the beginning of the experiment: mean $ATT_1 = 5.44$ ($SD = 1.35$); $ATT_2 = 5.41$ ($SD = 1.26$); $ATT_3 = 5.45$ ($SD = 1.26$).

3.3 Analytical Results

A mixed logit model was constructed for data analysis due to its ability to work with any distribution of random coefficients and approximate any random utility model (McFadden and Train, 2000). Moreover, mixed logit models are not subjected to the limitation imposed by the independence of irrelevant alternatives (IIA) assumption found in standard logit models. Because mixed logit allows “*for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time*” (Train, 2009), it takes into account plausible correlations among the 16 choices made by a single participant. For our model, the specification of the utility function of an individual i choosing a housing alternative j in a choice set t is as follows:

$$U_{jit} = c_j + \beta_1 Price + \beta_2 Positive reviews + \beta_3 FB friends + \beta_4 Common ground + \beta_5 Verified ID + \beta_6 Verified apartment photo + \mu_i + \varepsilon_{jit} \quad (5)$$

where μ is the normally distributed error component with mean zero and standard deviation σ_μ , which varies across participants i and alternatives j and embodies the correlations between observations obtained from the same respondent. The error component ε is assumed to have Gumbell distribution with mean zero and accounts for discrepancies among participants i , alternatives j and choice sets t (Pogtoglou et al., 2013). The statistical assessment of the mixed logit model was performed via SAS software (SAS, 2015) and assumed normal mixing distribution for price. First, to estimate how well the mixed logit model fits the data, we analysed various goodness-of-fit (GoF) indices. For a discrete choice model, the values of McFadden’s statistic in the range between 0.2 and 0.4 are accepted as good (Louviere et al 2000). Since we achieve a value of 0.26 for our model, an appropriate GoF can be presumed. Another frequently utilized measure – adjusted Estrella value which ranges from 0 (no fit) to 1 (perfect fit) – reached a level of 0.49, supplying further evidence of GoF (SAS Institute 2012).

The parameters of the model $\beta_1 - \beta_6$ and the constant c were estimated on the basis of our dataset. Beyond estimating the effect of different attribute levels on the overall utility, we further calculated participants' willingness-to-pay given a change in attribute levels (i.e., marginal willingness-to-pay, MWTP) using a price parameter included in our model. Specifically, assuming linear utility function, MWTP was computed as follows (Kjær, 2005, Ryan et al., 2008):

$$MWTP = \frac{\beta_{\text{attribute}}}{-\beta_{\text{price}}} \quad (6).$$

Summarized in Table 3, our findings proffer an interesting synopsis of the effectiveness of trust-enhancing cues explored in our study. Specifically, our estimation results show that the *number of positive reviews* emerges as the most effective trust-enhancing cue in our sample, with all levels having a significant positive impact on one's willingness to engage in a transaction. It appears that participants tend to treat the number of positive reviews on 'the more – the better' basis when choosing the housing alternative. Compared to the reference level, when 'no reviews are available', '5 positive reviews' ($\beta = 1.47, p < 0.0001$) are valued twice as much compared to just '1 positive review' ($\beta = 0.79, p < 0.0001$). Similarly, '15 positive reviews' ($\beta = 2.31, p < 0.0001$) are valued higher than '5 positive reviews'. In terms of price premiums, the availability of just one positive review is estimated at €9.45 as compared to the 'no reviews' scenario for the overall sample. Furthermore, 5 positive reviews are worth €17.72 whereas 15 positive reviews are valued at €27.76, which is close to the lowest price level of €35 being offered for the housing alternative. Together, this points to a prominent role of *feedback system* in enhancing consumers' trust in accommodation sharing.

Cues	Attribute	Attribute Level	Estimate	MWTP
Feedback System	Number of Positive Reviews	no reviews	Reference level	
		1 positive review	0.79**	€9.45
		5 positive reviews	1.47**	€17.72
		15 positive reviews	2.31**	€27.76
Social Graph	Number of Facebook Friends	no link to Facebook	Reference level	
		75 Facebook friends	0.12	€1.46
		200 Facebook friends	0.09	€1.07
		743 Facebook friends	-0.16*	€-1.89
	Common Ground	no common ground	Reference level	
		same university	0.22**	€2.60
Offline Verifications	Verified ID	not verified	Reference level	
		verified ID	1.47**	€17.72
	Verified Apartment Photo	not verified	Reference level	
		verified photo	1.04**	€12.57
Price			-0.08**	
GoF	Adjusted Estrella	0.49		
	McFadden's pseudo R-square	0.26		

Table 3. Model estimates. Note: Significant at **<0.0001; *<0.1 level; all values are rounded off to two places of decimals.

The effects of *offline verifications and telepresence* cues are also visible: both coefficients for the *verified personal ID* ($\beta = 1.47, p < 0.0001$) and for the *verified apartment photo* ($\beta = 1.04, p < 0.0001$) are highly significant. Interestingly, for the overall sample, MWTP for 5 positive reviews and for verified host's identity is identical at €17.72. Willingness-to-pay for the verified photo of the apartment is also high, reaching €12.57 for overall sample. At the same time, we observe that respondents only partially rely on cues grounded in *social graph*. The *number of Facebook friends* a host has does not significantly influence participants' decision to engage in a transaction. Moreover, the model offers a weak

confirmation that a large number of friends, which in our case is 743, may trigger suspicion ($\beta = -0.16, p < 0.1$). The influence of *common ground* (i.e., same university) is statistically significant but is relatively low ($\beta = 0.22, p < 0.0001$) with MWTP at €2.60 for this cue. Furthermore, as anticipated, *price* significantly influenced the choice of alternatives, but surprisingly, was not the most decisive factor for participants ($\beta = -0.083, p < 0.0001$).

3.4 Market Simulations

In the next step, we employed discrete choice analysis to predict consumer choices for predefined combinations of attributes using simulations. A market simulator considers what-if scenarios to examine new product design or improve product positioning and pricing strategy (Orme, 2010). Shares of preferences were predicted via mixed logit model in that the probability of choice is assumed to be a logit function of utility (SAS Institute Inc., 1993). Initial mixed logit estimates serve as a starting point for our analysis (see Table 3). In the first series of simulations (Figure 3), the effect of positive feedback was scrutinized given the positive impact of a feedback system determined in our study. Two alternatives were considered – a listing with ‘no reviews’ and a listing with ‘15 positive reviews’. To complete the choice set, the ‘no choice’ option was added as well. All other trust-enhancing cues were prefixed for both listings at ‘75 Facebook friends’, ‘host studied in the same university as you’ (abbreviated as ‘common ground’), ‘verified personal ID’ and ‘verified apartment photo’. Figure 3 depicts the market share of preference for the two listings *as a function of price of the listing with ‘15 positive reviews’* (price of the listing with ‘no reviews’ was fixed at €35). Except for the first simulation round when pricing levels are equal (€36), our results reveal participants’ behaviour when they are confronted with ‘trustworthiness vs. price trade-off’. By reducing information asymmetries and thereby enhancing trust, the presence of ‘15 positive reviews’ bolsters the attractiveness of the listing so much so that it dominates the market for pricing levels between €35 and €55. Only when pricing levels shot above €65 per night will the listing with ‘15 positive reviews’ lose its market leadership. This is because half of the participants (50%) on our simulated sharing platform will take a risk and prioritize a significantly cheaper (€35) room without any reviews. Findings from our market simulations thus suggest that consumers, despite attributing considerable value to a feedback system, may be willing to compromise when the monetary stakes become prohibitively high.

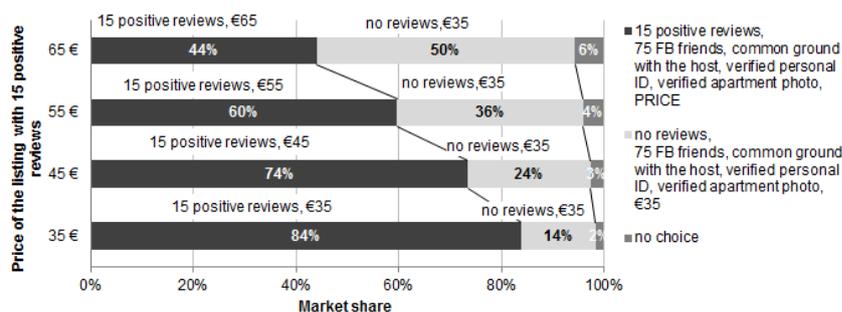


Figure 3. Market share simulations 1.

In the second series of simulations, a trade-off between different types of trust-enhancing cues was explored by focusing on two offerings – a listing with a verified personal ID and a listing without it – and varying the number of positive reviews received. This particular combination of cues was selected for investigation due to their importance for the overall sample. For a listing without a verified personal ID, the number of positive reviews varies from 0 to 15 as can be seen on the vertical axis of Figure 4. Conversely, for a listing with a verified personal ID, the number of reviews is set to 0. ‘No choice’ option was included as well. All other trust-enhancing cues were kept homogeneous for both listings. We observed that when both listings are not reviewed, an offer with a verified personal ID is preferred by 65% of participants. Just ‘1 positive review’ alone does not convince the majority to switch to a listing without ID verification. However, a listing with ‘15 positive reviews’ dominates the

market, dwarfing the value attached to a *verified personal ID*. Our market simulations thus suggest that consumers, despite valuing personal ID verification, are inclined to trust independent reviews when their numbers become sufficiently large.

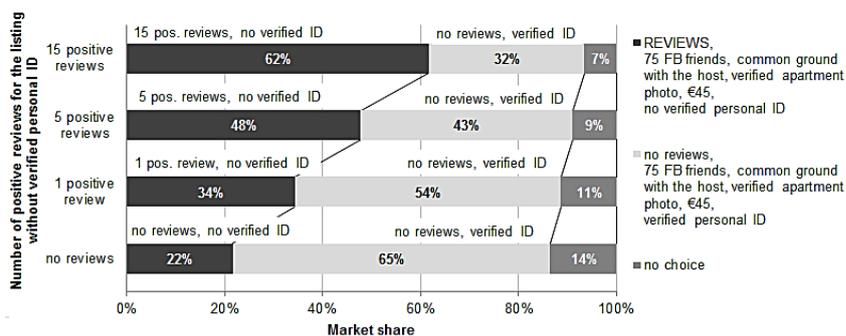


Figure 4. Market share simulations 2.

4 Discussion, Implications and Concluding Remarks

Building on the Signalling Theory (Akerlof, 1970), this study sets out to investigate the effectiveness of trust-enhancing cues in affecting consumers' willingness to transact on accommodation sharing platforms under conditions of uncertainty. Consistent with prior research (Wang et al, 2004; Wells et al., 2011; Zervas et al., 2015; Möhlmann, 2016), our findings attest to the cruciality of cues in building trust, which in turn culminates in desirable behavioural outcomes like intention to transact and willingness to pay. First, we demonstrate that even though consumers do trade-off between trustworthiness and price (see Figure 3), *feedback system* fully accomplishes its trust-enhancing function. In line with our empirical findings, the *number of positive reviews* emerges as being instrumental in shaping consumers' decisions about which listing to rent from. Consumers appear to rely on the heuristic of 'the more – the better' with higher numbers of positive reviews culminating in higher price premiums. Compared to listings with *no reviews*, consumers are willing to pay €27.76 extra for a listing with 15 positive reviews. Second, *offline verifications* have also been proven to embody trust-enhancing capabilities. In contrast to unverified listings, both *verified personal ID* and *verified apartment photo* emerge as significant drivers of accommodation sharing transactions, prompting consumers to pay €17.72 and €12.57 extra respectively. Interestingly, our results suggest that the trust-enhancing capability of *verified personal ID* is equivalent to the effect of 5 *positive reviews*. All in all, in line with the work of Ba et al. (2003) and Finley (2013), our findings testify to the importance of expanding and enforcing platform verification frameworks because such measures seem to be valued by consumers. Third, surprisingly, cues grounded in *social graphs* exhibits only marginal significance. Although the presence of a *common ground with the host* has a positive impact for the overall sample, its contribution and related price premium are comparatively small unlike results reported by Finley (2013). At the same time, the *number of Facebook friends* was generally disregarded by consumers.

Several caveats in the interpretation of our empirical findings should be mentioned. First, we concentrate solely on the quantitative aspects of feedback systems (i.e., number of reviews) because the qualitative (or semantic) components of feedback are beyond the scope of our study. Moreover, only positive reviews were considered. While negative reviews are very rare on sharing platforms (Zervas et al., 2015), it is still a limitation that should be addressed in future research. We also render the face of the host and reviewers unidentifiable to participants even though we acknowledge that past studies have supplied evidence attesting to the impact of facial expressions on trusting beliefs (e.g., Steinbrück et al., 2002). Likewise, we kept the platform name fictional to avoid branding effects. Finally, our sample comprises primarily of German students. While students constitute an important customer segment for accommodation sharing platforms, we encourage future studies to replicate our work with a more representative sample.

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