Price Determinants on Airbnb: How Reputation pays off in the Sharing Economy

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Abstract

Trust is a crucial prerequisite for peer-to-peer rental and sharing. Therefore, platform operators such as Airbnb have implemented a plethora of trust-building mechanisms, user interface (UI) artefacts, and reputation systems. While the role of reputation systems for establishing trust is well-understood, little is known about how reputation actually translates into tangible economic value, either by attracting more demand or by enabling the enforcement of higher prices. In this paper, we consider the economic value of trust-building artefacts on Airbnb by quantifying price effects of common reputation features from a signaling theory perspective. Our analysis is based on hedonic price modelling and a large-scale dataset from 86 German cities that provides insights in the price effects of a diverse set of variables (average rating score, number of ratings, Superhost status, ID verification, photos, and duration of membership). Employing hedonic price regression modelling, we find that index signals such as the hosts' rating scores and duration of membership are associated with economic value. Moreover, also conventional signals such as accommodation photographs consistently translate into price premiums. We discuss implications for platform operators, users, and the general design of Information Systems (IS) artefacts intended to facilitate peer-to-peer platform interactions.

Keywords Airbnb, Trust, Reputation, Sharing Economy, Peer-to-Peer Platforms, Signaling Theory

Introduction

The worldwide economic importance of the sharing economy has grown rapidly over the last decade (Sundararajan 2016). Peer-to-peer (P2P) platforms allow users to offer products and services while the platform operator manages and maintains the marketplace (Botsman and Rogers 2010). Platforms for P2P accommodation sharing have experienced particular strong growth and represent an important sub-domain within the broader sharing economy landscape (PwC 2015). One of the most popular and frequently discussed examples for this phenomenon is Airbnb (Guttentag 2015), with over 3 million listings in 65,000 cities and 191 countries worldwide, facilitating an average of 500,000 stays per night, and, since its foundation in 2008, has been used by over 150 million guests (Airbnb 2017). Similar accommodation sharing services are offered by competitors such as Flipkey, Homestay, Roomora, and Wimdu/9Flats.

In contrast to the traditional hotel industry, consumers on Airbnb face the need to market themselves as trustworthy individuals in order to be granted a permission to book (Karlsson et al. 2017). Likewise, platforms such as Airbnb enable private individuals to take on the role of micro-entrepreneurs and act as hosts, offering their accommodation to tourists or business people for a charge (Sundararajan 2014). In fact, depending on location and apartment type, hosts on Airbnb can generate a significant income by temporarily renting out either a shared room, a private room, or their whole apartment for a few days, weeks, or even months (Jung et al. 2016). Hosts' overall capability to generate income evidently depends on how much demand they are able to attract at a specific price. In order to convert an interested user's attention into a tangible booking request, trust is hence crucial (Gebbia 2016; Hawlitschek, Teubner, and Weinhardt 2016). Therefore, a host's overall appearance, including profile and product pictures or information on the hosting track record, is of high importance (Ert et al. 2016). Since the entire process of exploring and booking is conducted online, the elements displayed via Airbnb often serve as the single point of reference for potential guests to initially assess a host's trustworthiness and the corresponding offer's quality (Hawlitschek, Teubner, Adam, et al. 2016). The financial success of hosts is thus immediately rooted in their representation on the platform, rendering the design elements used in this regard an interesting subject to economic and IS research. In this, a plethora of factors was found to drive consumers' intentions to (re-) use Airbnb, including aspects of trust, authenticity, familiarity, and product variety (Hawlitschek, Teubner, and Gimpel 2016; Möhlmann 2015; Liang et al. 2016). Within the scope of this paper, we thus address the following research agenda. First, we seek to quantitatively assess the structure of supply and the corresponding users on Airbnb, that is, provide a sociographic analysis of Airbnb's user population. Second, we then address the question, how typical UI artifacts of the Airbnb reputation system translate into economic value in form of price premiums.

As outlined above, one central concept in this paper is trust, a complex construct, which has received much attention from various research domains (Rousseau et al. 1998), ranging from philosophy, sociology, psychology, neuro-sciences, economics, computer science, and information systems. Elaborating on all aspects and facets of trust is hence far beyond the scope of this paper. Here, trust is thus conceptualized as a consumer's willingness to rely on a host's actions and intentions, which can be further separated into the trusting beliefs of ability, integrity, and benevolence (Hawlitschek, Teubner, and Weinhardt 2016). Reputation as a potential antecedent of trust, in contrast, captures the hosts' tangible record of prior host-guest interactions, as well as other characterizing factors (e.g., duration of membership, measures of identity verification and self-description)

(Ma et al. 2017; Zervas et al. 2015). With this work, we contribute to the existing body of literature on the sharing economy by demonstrating price effects of scores in different reputation measures, based on actual Airbnb data from 86 German cities. More specially, we show that hosts' average rating scores, a longer duration of platform membership, and a more extensive representation by apartment photos are reflected in price mark-ups which we establish from a signaling theory perspective.

The remainder of this paper is organized as follows. In Sections 2 and 3, we review related work and derive our research model and hypotheses. In Section 4, we describe our dataset, method, and present our main results. In Section 5, we then discuss limitations, future work, and the implications regarding the economic value of reputation. Section 6 summarizes and concludes this paper.

Related Literature

In recent years, multiple strands of scientific literature on the sharing economy have evolved across several IS-related fields, covering subjects such as consumption practice, innovation, lifestyle and social movement, the sharing paradigm, and trust (Cheng 2016). Trust is considered to be of particular importance for the sharing economy and especially for P2P markets (Belk 2010; Botsman and Rogers 2010; Ert et al. 2016; Hawlitschek, Teubner, and Gimpel 2016; Strader and Ramaswami 2002). Consequently, P2P platform operators have implemented mechanisms and signals to facilitate the formation of trust between providers and consumers (Resnick and Zeckhauser 2002; Zervas et al. 2015), including identity verification, mutual rating and review schemes, insurances, and specific web design techniques (Gebbia 2016; Teubner 2014). Reputation and electronic word of mouth thereby help to assess the trustworthiness of peers in electronic communities (Xiong and Liu 2004).

Compared to traditional e-commerce where an impeccable reputation can lead to an increase in product sales, that is, in volume (Chevalier and Mayzlin 2006), hosts on Airbnb are limited in terms of how much of their products and services they can sell. More specifically, an apartment can at most be rented out 365 nights per year. Consequently, an increase in requests due to positive reviews or ID verification may eventually not be reflected in additional sales, but rather in higher posted prices. Related research provides support for this assumption, showing that hosts on Airbnb actively capitalize high reputation either by choosing guests more selectively or demanding higher prices (Gutt and Herrmann 2015; Ikkala and Lampinen 2015).

Several recent studies have set out to further explore prices and pricing decisions on Airbnb. Edelman & Luca, (2014), for example, employ individual price differences to study racial discrimination on Airbnb. Their data suggests that Afro-American hosts are forced to charge lower prices than white hosts for comparable apartments by a residual of 12%. A follow-up study considers the opposite market-side and finds that booking requests of users with typical white names are accepted 16% more often than those of users with typical Afro-American names (in the absence of profile photos), speaking in favor of the existence of racial discrimination on Airbnb (Edelman et al. 2017). Also, a related study on racial discrimination by (Kakar et al. 2016) finds Hispanic and Asian hosts to charge lower prices compared to their white counterparts. Using linear regression modelling, the authors also show that positive ratings and the Superhost badge have positive price effects. The issue of discrimination was recently picked up by the media and also Airbnb felt compelled to implement counter measures.[1] Moreover, Ikkala & Lampinen (2014) conducted interviews to explore the relationship between Airbnb reputation and pricing decisions. Ikkala and Lampinen (2015) then considered how hosts approached this matter specifically. Their results suggest that hosts rent out for financial, but also for reasons of social interaction. Hosts participating in the study stated to actively exploit their reputational capital (e.g., reviews), either by increasing price or by accepting guest requests more selectively. Gutt & Herrmann (2015) considered the effect of rating score availability. Based on ~14,000 listings, they analyzed price differences before and after a host's average rating is publicly displayed for the first time. This happens as soon as a host has collected three ratings. Here, hosts were found to monetize rating availability by a mark-up of €2.69.

Besides such direct trust-related scores, user representation is also considered important. Teubner et al. (2014), for instance, showed experimentally that user photographs and avatars bear the potential to foster trust. Similarly, Fagerstrøm et al. (2017) find that negative and absent facial expressions of Airbnb hosts evoke avoidance tendencies and decrease their (hypothetical) chances to rent out their listing in a scenario-based survey. Ert et al. (2016) considered the impact of user photographs for trust building, prices, and booking probabilities based on the hedonic price model (Rosen 1974). They find that visual-based trustworthiness (assessed by Amazon Mechanical Turk workers) drives listing prices, whereas host attractiveness and review score do not. This analysis, however, is based on 175 observations from Airbnb listings in Stockholm (Sweden), only. In a complementary experiment, the authors find that Internet users exhibit an increased likelihood to choose Airbnb listings from trustworthy, attractive, and well-reviewed hosts.

Beyond the hosts' visual appearance, Airbnb has created a dedicated tool for reputation building based on post-transactional and mutual peer reviews. Slee (2013) as well as Zervas et al. (2015) pointed out a marked property of this (and other platform's) 5-star rating systems. Rarely any review, and hence rarely any average rating score, falls below four out of five stars. In fact, more than 95% of Airbnb's listings (Zervas et al. 2015) and virtually all of the rated BlaBlaCar rides exhibit 4.5 or 5.0-star scores, implying little discriminating power of star ratings. Similar figures are reported by Gutt and Kundisch (2016). Fradkin et al. (2017) suggested two explanations for this imbalance. First, consumers may prefer to give positive reviews due to a natural human tendency to avoid conflict and seek states of harmony and well-being. Second, personal interaction with the host may create social restraints to provide negative review. Another explanation is provided by Mulshine (2015), suggesting that hosts not only get to see the reviews their potential future guests *received*, but also those they *wrote*. Hence, guests may withhold negative feedback, because they fear that future hosts might be reluctant to rent to them, as they would have to anticipate to receive an all too honest review, too.

Recent research both from Information Systems and the Hospitality Management discipline has begun to consider Airbnb specifically. Ma et al. (2017), for instance, analyze hosts' self-description on their corresponding profile pages. They show that hosts can influence the perceived trustworthiness by strategically disclosing different topics (e.g., with regard to their work, educational background, or interests). Concerning the analysis of host profiles, Liang et al. (2017) in particular focus on the impact of Airbnb's Superhost badge. This distinction is given to hosts for meeting particular benchmarks specified by Airbnb (i.e., high response rate, consistent 5-star evaluations, experience, and commitment). As they outline, hosts can leverage this badge by setting higher prices without losing as much demand (as compared to hosts without the Superhost badge). In

[1] http://www.bbc.co.uk/news/business-37314230

contrast, Karlsson et al. (2017) analyze parameters in booking requests that influence the likelihood of being granted permission to book. Their guest-focused analysis shows that the response is not only affected by trip-related attributes (e.g., number of nights, motivation for the trip) but also personal characteristics (e.g., gender, age, profile picture). Moreover, Ke (2017) conducted a large-scale analysis of 2.3 million Airbnb listings. In this, aspects such as location, room type, star ratings, and reviews are utilized to expose factors that determine a listing's future rental performance, approximated by the number of new ratings. The author finds that private rooms, listings that can be booked instantly, and users with Superhost status gain more reviews. Also, listings from hosts with high response rate, short response time, and smaller number of managed listings receive more reviews. At the same time, entire homes and shared rooms receive less reviews. Comparably, Wang and Nicolau (2017) investigate the price determinants of Airbnb rentals. They outline that, compared to the traditional hotel industry, different attributes determine prices for accommodation. Starting off from the fact that traditional price indicators from the hotel domain (e.g. the hotel star classification as issued by the HOTREC in the European Union and chain affiliation) do not apply to peer-based accommodation sharing, their analysis reveals that 24 out of 25 variables within five categories (host attributes, site and property attributes, amenities and services, rental rules, and number of online reviews and ratings) are good predictors of price. Gutt and Kundisch (2016) show that specifically Airbnb's price/value ratings offer a valuable source of information for potential buyers in the sharing economy, where increases in listing prices are associated with decreases in these value-for-money scores.

The limited variety in average rating scores renders other, trust-related UI artifacts and measures all the more relevant. In this work, we set out to explore the economic value of different trust and reputation measures based on actual market data. Specifically, we focus on average rating score, number of ratings, ID verification, duration of membership, Airbnb's Superhost badge, and the number of accommodation photos provided. Following the approach of Ert et al. (2016), our analysis is based on the hedonic price model (Rosen 1974), suggesting that Airbnb's market is in a (hypothetical) state of equilibrium where hosts set individual prices exactly as high as they can – based on their own and their listing's properties.

From the perspective of the tourism management literature, typical price determinants for traditional hotels are hotel location (where shorter distances to focal points such as city center, major attractions, or beaches are associated with higher prices), and hotel category, amenities, and services (i.e., from budget to luxury) (Wang and Nicolau 2017). In addition to these important control variables, we suggest that on platforms such as Airbnb, provider-specific factors will play a role for pricing as well, and that in particular reputational factors are important. We contend that sharing economy platforms represent a suitable test bed for studying price effects by hedonic price models, due to three reasons. First, the very nature of P2P platform economics with its many de-central actors and its high frequency of bookings creates an ideal environment for competition and price discovery processes. Second, sharing economy interactions are conducted on a personal, that is, non-professional basis. This makes personal attributes such as the hosts' reputation scores more salient, since the conventional mechanics of brand building and regulation do not apply. And indeed, the lines between private and professional spheres are blurring, where (1) Airbnb has become a platform and marketing channel for both private and professional providers, and (2) many providers run semi-professional businesses by renting out their guest room(s) or entire apartment with high frequency and lucrative prices. Now, along with this, sharing economy platforms illustrate products and services and the corresponding users by rich profiles including explicit social cues (e.g., photographs, self-descriptions, text reviews), constituting a prerequisite and a powerful basis for price differentiation. Third, platforms provide a corset for their users' diverse content. Hence, virtually all listings on Airbnb are presented within a uniform template and contain the same informational bits and pieces. This renders the effects of investigated factors highly comparable across large sets of accommodations and hosts.

Research Model & Hypotheses Development

In order to investigate the price effects of different artefacts on Airbnb, we propose the stylized research model presented in Figure 1. Our reasoning is based on signaling theory which we outline in the following (Spence 2002). In the subsequent paragraphs, we then derive and underpin our hypotheses.

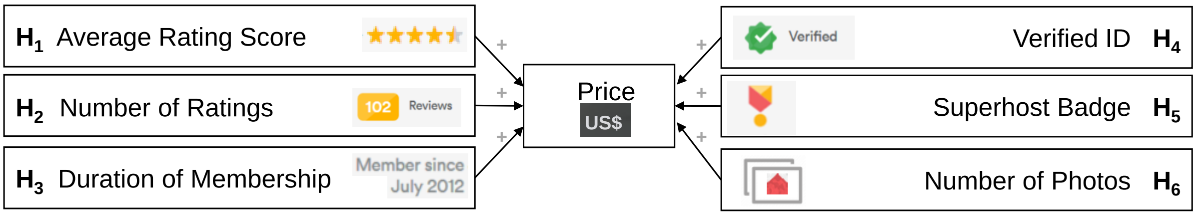

***Figure 1**: Research model*

Signaling theory focuses on asymmetries of information between at least two different market sides (e.g., hosts and guests), during the initiation of transactions. To resolve existing informational asymmetry and to promote the exchange, providers can signal the quality of their product or service by indicators such as price, descriptions, guarantees, or branding (Basoglu and Hess 2014). Signals can be classified as conventional, handicap, or index signals (Berger and Calabrese 1975; Spence 2002). First, *conventional signals* (such as self-descriptions, promises, etc.) are considered the least reliable, as they are usually easy to create, hard to verify, and let much room for deception ("cheap talk"). In contrast, the creation of *handicap signals* (e.g., a well-crafted CV or a product guarantee), is associated with effort either before or in the aftermath of a transaction. In particular, such signals will be more costly for providers of low than of high quality (e.g., because their product has a higher chance to fail) and can thus effectively be interpreted by potential consumers. Lastly, *index signals* rely on some form of confirmation through an independent third party which has actually used or experienced the product or service and does usually not have any incentive to falsely report its quality. Index signals are hence widely considered the strongest type of signals (Aiken and Boush 2006).

All signals considered in the context of this study represent handicap or index signals, as they are either associated with effort or based on external evaluation. Rating schemes (including average rating score and number of ratings) and performance-dependent badges (such as the Superhost badge) represent a genuine form of index signals. They are a common approach to establish trust on sharing economy platforms (Teubner 2014). They quantify and aggregate the experiences of users from past transactions as an indication of trustworthiness, as actual trustworthiness is unknown to potential guests prior to booking (Resnick and Zeckhauser 2002).

The influence of ratings on listing price (H_1, H_2)

User ratings are commonly found as effective antecedents of trust between peers (Bente et al. 2012; Fuller et al. 2007). Moreover, empirical evidence suggests that different levels of reputation, based on rating scores, translate into different prices (Edelman and Luca 2014). For Airbnb, these authors analyzed the star rating's different subcategories, including scores for location, check in, communication, cleanliness, and accuracy. Within various linear regression models, they consistently found higher reputation scores to be associated with higher listing prices. Similar results are reported by Wang and Nicolau (2017), finding that an additional star is associated with a price markup of 0.87% per star. Also Gutt and Herrmann (2015) showed that Airbnb listings in New York exhibited price mark-ups by an average of approximately US$ 3, after the website displayed a public star rating for the corresponding host for the first time. Ikkala and Lampinen (2014, 2015) found that Airbnb hosts intend to capitalize on ratings, either by increasing prices or by accepting requests guests more selectively. The significant price effect of high ratings within Airbnb is consistent with findings from other settings such as online book or shop reviews (Chevalier and Mayzlin 2006; Luca 2016). We hence propose that a host's rating eventually translates into higher listing prices:

H_1: *Higher average rating scores are associated with higher listing prices*.

With regard to the *number* of past transactions, we expect a similar effect. Common sense and signaling theory suggest that a higher rating count renders average scores more reliable, hence more trustworthy. Accordingly, Guo et al. (2014) argue that the amount of trust information increases with greater numbers of ratings. A low number of ratings may raise reliability doubts for several reasons, e.g., ratings may be acquired by friends and family only and are naturally providing a lower level of confidence. Moreover, a high number of ratings points to consistency and experience as a host. Empirical evidence on this matter is sparse. Ert et al. (2016), for instance, do not find any significant price effects on Airbnb based on the number of ratings. Their analysis, however, is only based on 175 listings from Sweden, which may be a too small dataset to draw reliable conclusions from. Wang and Nicolau (2017), in contrast, find negative effects, where overall, each review (per year) is associated with a markdown of 0.1%. In related contexts, Duan et al. (2008), for instance, find that box office revenues *are* correlated with the number of user postings regarding a specific movie. Revenues here serve as a proxy for trust, since moviegoers normally face some degree of uncertainty regarding how much they will have liked the movie in hindsight. The authors' data suggests that many user reviews are not only an indicator, but also an influencer of revenues. Our second research hypothesis thus reads:

H_2: *Higher numbers of reviews are associated with higher prices*.

Note that it is well-conceivable that there occurs an interaction effect between the average rating score and the underlying number of ratings. Based on the aforementioned notion that better ratings are particularly valuable if reliable, that is, based on a higher number of ratings, a possible interaction should be positive. This effect is addressed in the empirical model.

The influence of the membership and ID verification on price (H_3, H_4)

Airbnb explicitly displays *since when* a user is registered on the platform. This *duration of membership* is illustrated close to fundamental profile information such as name and photo. Since Airbnb actively seeks to create a community of long-term engagement (Gebbia 2016), membership duration may be beneficial for the reputation of the host, being an established and acknowledged member of the community, and hence could impact a listing's price. We suggest this to be based on two effects. First, membership duration may serve as a handicap signal of trust since long-exiting accounts require long-term engagement, thus are time-costly, and are hence less likely to be fraud. In contrast, think of encountering a profile which has only been created few days ago; it inevitable conveys the feeling of serving another, potentially fraudulent, purpose. Second, with an increasing experience due to a longer lasting membership, hosts may learn to adapt to the market and to set the individual optimal (i.e., highest achievable) price. Furthermore, following the notion that in some facets, the sharing economy may build social capital (Schor 2016), one may argue that increased social capital can positively influence consumers' satisfaction with providers (Huang et al. 2017). Since time is one of the key enablers for the development of social capital (Nahapiet and Ghoshal 1998), we therefore argue that longer durations of membership can positively influence listing prices through the monetization of social capital (Orlowski and Wicker 2015). We thus hypothesize:

H_3: *A longer duration of membership is associated with higher prices.*

Furthermore, Airbnb allows its users to verify their identity by scanning ID card and face via webcam (currently offered by *Netverify*, Jumio.com). Once approved, a badge credits authenticity to the user. This requires some effort. Also, verified users signal their (increased) willingness to be held accountable for their actions. They voluntarily increase the cost of own malicious behaviors (self-commitment). User verification was found to increase trust, for instance for the case of online dating (Norcie et al. 2013) and as a security feature in a hotel booking process may result in a customer's willingness to pay price premiums (Feickert 2006). The importance of genuine and reliable online identities is also illustrated by the efforts taken by platforms such as eBay to avoid users to create multiple, potentially mal-intended accounts (Resnick and Zeckhauser 2002). We therefore suggest that the effect of ID verification can be commercialized in the context of Airbnb, too:

H_4: *Verified IDs are associated with higher prices.*

The influence of Superhost status and Photos on price (H_5, H_6)

Besides such user-driven trust signals, Airbnb's Superhost badge represents a status signal for hosts of outstanding quality. The badge is automatically awarded to hosts who have accommodated 10 or more guests over the course of one year, received a share of at least 80% 5 star ratings, have an answer rate of at least 90%, and did not cancel any confirmed bookings (Airbnb 2014). Especially knowing whether a host cancelled confirmed bookings in the past represents a valuable information to guests, as it makes trips less imponderable and booking hence more reliable. Moreover, a high answer rate signals a well-organized host. Overall, the Superhost badge is a signal of outstanding quality and could hence help to build reputation. It is issued by an independent party (Airbnb) and – by displaying a visible badge – draws attention of potential guest to the awarded listing (Liang et al. 2017). In addition, Airbnb even offers an option to search for listings by hosts with "recognized hosts," that is, with Superhost status. Naturally, hosts with Superhost status can be expected to exhibit a higher number of ratings and higher average rating scores, thus pointing to issues of collinearity. It must be said, however, that only around 12% of all listings are operated by hosts with Superhost status, and that – in light of how this status is awarded – it reflects a special and rare combination of other, positive properties. Analogous to our reasoning above, we suggest that hosts utilize this capital for price premiums. Corresponding empirical evidence is found by Wang and Nicolau (2017), reporting a price markup of 8.73% based on the Superhost status. Our fifth hypothesis thus states:

H_5: *Superhost badges are associated with higher prices.*

Lastly, photos of one's apartment represent a conventional, yet informative signal of what a guest can expect and, given a high photo quality, can be monetized in additional earnings (Zhang et al. 2016). A higher number of photos usually allows for a better assessment of the apartment's character, style, its different rooms, facilities, and details. This renders concealing actual apartment quality more difficult and thus reduces the risk for the potential guest. Similar positive *diagnosticity* effects are known from various e-commerce studies (e.g., Jiang and Benbasat 2007). We hence hypothesize:

H_6: *A higher number of apartment photos is associated with higher prices.*

Airbnb Data Analysis

Our analysis is based on a dataset of Airbnb listings from the 86 largest German cities, obtained by combining several techniques of data collection. First, we harness web crawling techniques to gather publicly available information on existing Airbnb listings, yielding a total of 15,198 listings. Second, we combine and enrich this data with information from other sources such as Google's API, Microsoft's face and emotion APIs, city rent price levels, and population statistics. Since, for each listing, Airbnb also indicates a rough location (based on latitude and longitude), we are able to include a measure for "distance to city center," as a proxy of how well a certain apartment is located within a city. We only consider listings with three or more ratings, for which Airbnb provides star ratings. Additionally, to increase the comparability among considered listings, we decided to exclude accommodations suitable for only one or more than six guests (i.e., hostels, hotels, and large-scale dormitories). The final dataset then included 13,884 listings. For each listing, we investigated attributes from the following categories: (1) reputation, (2) apartment, (3) city, (4) convenience, and (5) personal. Table 1 displays a summary of all used variables, including mean, standard deviation, and quantiles. The corresponding correlation matrix (with Pearson correlation coefficients) is provided in in Table A1 in the Appendix. Moreover, we checked for multi-collinearity among the independent variables to avoid any undesired effects on the regression results. Variance inflation factors (VIF) were applied to rule out such effects. As can be seen in Table 1, with a maximum VIF of 1.265, even a conservative criterion (VIF ≤ 4) is met and multi-collinearity should hence not be an issue (Pan and Jackson 2008).

***Table 1**: Summary of variables*

	Mean	St. Dev.	VIF	MIN	25Q	50Q	75Q	MAX
Price (US$)	159.899	87.016	-	26	108	141	187	1945
Average Rating Score	4.682	.363	1.135	0.0	4.5	4.5	5.0	5.0
Number of Ratings	20.753	26.996	1.208	3	5	11	24	302
Superhost	.116		1.131					
ID verification	.586		1.050					
Membership (months)	27.865	15.771	1.265	2	15	26	40	90
Number of Photos	14.170	9.068	1.223	1	8	12	18	134
Apartment Size	2.868	1.155	1.222	2	2	2	4	6
Type: Entire Home	.655		1.213					
Type: Private Room	.327		-					
Type: Shared Room	.010		-					
Distance to City Center (km)	3.042	2.029	1.221	0.027	1.618	2.688	4.015	21.353
Response Time < 1h	.358		1.208					
Deposit required	.384		1.158					
Check in/out comfort	.242		1.028					
Minimum stay	2.386	6.061	1.041	1	1	1	2	190
Instant booking	.135		1.182					
Cancellation strictness level	.875	.769	1.129	0	0	1	1	2
Gender: female	.525		1.034					
Has multiple listings	.228		1.167					
Face visible	.739		1.017					
Age (Microsoft API)	37.152	11.153	1.111	0	29.8	35.1	42.7	91.8
Smile (Microsoft API)	.277	.368	1.012	0	.005	.068	.451	1

Attribute Categories

Reputation attributes: This category contains the focus variables of this study, including Average Rating Score (1 to 5 stars in steps of .5 stars), number of ratings (≥ 3), ID Verification (binary; 1=yes, 0=no), Duration of Membership (in months), Superhost status (binary; 1=yes, 0=no), and the number of apartment photos (≥ 1).

For a better understanding of Airbnb's population (users and listings), Figure 2 depicts the distributions of price (2 persons, 2 nights, including cleaning fee), number of listings (per host), average rating score, number of ratings, duration of membership, and number of apartment photos. Overall, prices are distributed fairly normal around the median of 141, whereas several outliers with high prices drive up the mean to 159.90. As noted in the literature earlier, the distribution of star ratings is skewed, where practically all ratings are either 5.0 (47.4%), 4.5 (43.9%), or 4.0 (6.9%) stars. On average, the listings have collected 20.75 ratings which, again, is driven by few listings with many ratings. Half of all listings have 11 or less ratings. The average number of provided apartment photos is 14.17. Moreover, 11.6% of the listings are offered by users with Superhost status, 58.6% by users with verified ID. The average duration of membership 27.87 months.

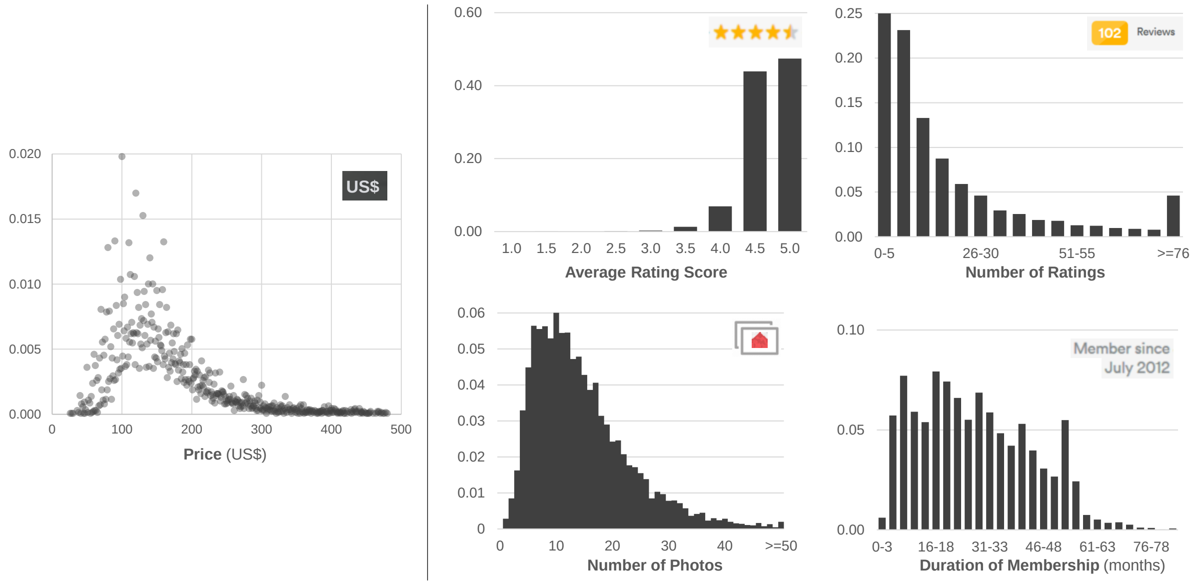

***Figure 2**: Distributions of main non-binary variables*

Apartment attributes: This category includes all (physical) aspects immediately associated with the apartment. Size is usually described by the (maximum) number of guests it is suitable for. Since we considered listings of size between 2 and 6 to exclude dormitories, this value was limited to this specific range, yielding an average of 2.87. Moreover, providers on Airbnb offer different types of accommodations, including shared rooms (i.e., the couch in the living room, 1%), private rooms (i.e., guest rooms, 32.7%), and entire apartments (65.5%). In the regression models, the first is benchmarked against both other categories.[2] Besides these aspects, the value of real estate strongly depends on location. Hence, we included the listing's distance to the city center as a control variable. Since geographic data is provided as latitude/longitude coordinates, the distance measure is computed using the haversine formula, which is used to calculate the distance between two points on the surface of a sphere. Average distance to city (across all 86 cities) center was 3.042 km.

City attributes: Beyond the apartment's properties, the city themselves may have important impacts on price. In order to control for such dependencies, this category contains the general rent price level of a given city (€/m²; as provided by a German platform for real estate brokerage), as well as the logarithm of population (inhabitants). Figure 3 depicts the listings' distributions for selected cities.

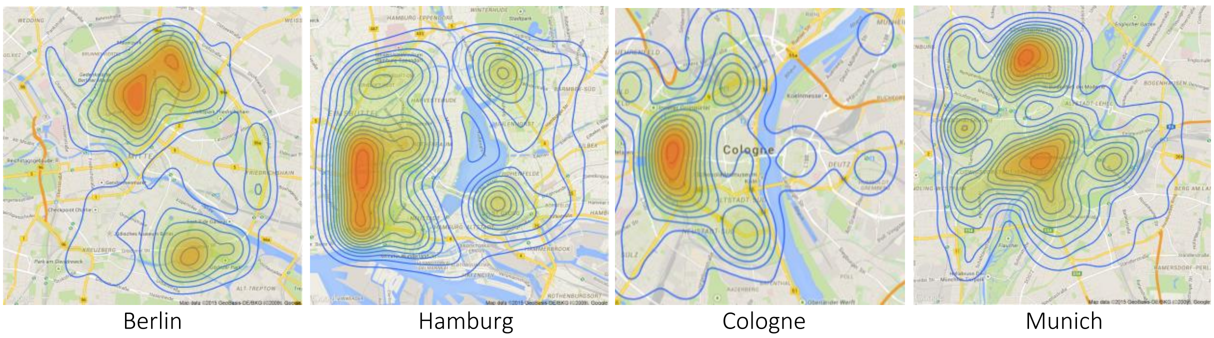

***Figure 3**: Distribution of Airbnb listings in four selected cities (Berlin, Hamburg, Cologne, and Munich)*

[2] Note that a more detailed differentiation with two dummy variables would not be very reasonable in view of regression robustness here since the "shared room" category applies to only ~1% of the data.

Convenience attributes: This category includes options the hosts may or may not offer for the guest's convenience or that emerge from their past behavior but indicate a high level of comfort. This includes the option for instant booking (which is offered by 13.5%), deposit requirement (required by 38.4%), cancellation strictness (0 = flexible, 1 = medium, 2 = strict), as well as the minimum possible duration of a stay (2.37 nights on average). Moreover, some host allow for early check-in or late check-out which is coded binary as check in/out comfort (provided by 24.2%). Furthermore, this category includes whether a host typically answers requests fast (i.e., within 1 hour), which is the case for 35.8% of all hosts.

Personal attributes: This category includes a host's personal attributes such as gender (inferred from name, manually classified, 52.5% female), whether multiple listings are offered (22.8% do so) and profile image (i.e., whether at least one face was clearly visible or not, 73.9%). Provided that the profile image depicts a face, we applied Microsoft's Emotion API to further assess the host's age and the degree of smile. Average estimated age was 37.152 years with a standard deviation of 11.153 years. Average assessed degree of smile (on a scale from 0 to 1) was .277 with a standard deviation of .368.

Price regression models

To assess the attributes' economic value, we conducted a set of linear regressions (I to VI). As dependent variable, we used the price of a stay for two persons and two nights (including cleaning fee), depicting a quite common travel scenario. Hedonic price modelling assumes that marketable product features will be reflected in the products' market prices (Ert et al. 2016; Rosen 1974), and that by regression analysis, the individual impacts of certain features can be quantified. To assess robustness, we conducted multiple regressions with varying sets of control variables. The fundamental apartment properties are used as a core set of independent variables for all models. Table 2 summarizes the main results, revealing positive, significant, and consistent effects of average rating score (H_1), duration of membership (H_3), and number of photos (H_6). Specifically, an increase by one star is associated with an average price markup of 18 US$ (model I). Accordingly, one moth of membership translates into a markup of about 0.5 US$ and the display of an additional apartment photo in 1 US$, respectively. In contrast, the effect of ID verification and Superhost status are insignificant (or unstable at best) and fluctuate depending on the set of included control variables (H_4 and H_5). Interestingly and in contrast to hypothesis H_2, we find a *negative* (significant and consistent) association of number of ratings and price throughout all models. Moreover, there exists significant interaction between average rating score (ARS) and number of ratings (NoR), meaning that the negative effect of number of ratings on listing price is stronger for apartments with lower average rating scores (decreasing with a rate of -.27 US$ per rating in the 5.0-star case as opposed to -.54 US$ and -.81 US$ per rating in the 3.0 and 4.0-star case, respectively). Likewise, the effect of an additional star is stronger for increasing rating counts (see Figure 4).

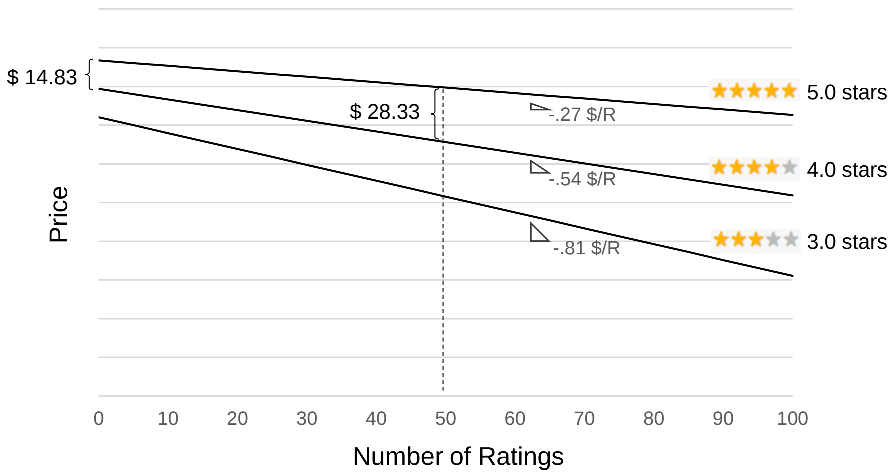

***Figure 4**: Interaction effect visualization (based on regression model II)*

The examination of the other attribute categories reveals, quite expectedly, that larger apartments are more expensive than smaller ones, entire homes are more expansive than private rooms or shared apartments, and also that distance to city center is a significant price determinant where centrally located listings yield higher prices than those further outside (5.29 – 7.63 US$ per km). Moreover, listings in larger cities exhibit higher prices.

With regard to the convenience attributes, there do not occur significant price effects, with exception of deposit requirement and cancellation strictness, where both factors are associated with higher prices. In these cases, causality is very likely to work in the opposite direction, however. Hosts of more expensive listings are simply more likely to require deposits, for instance as a quasi-insurance for their high value furnishings. Also, it is conceivable that premium listings have stricter cancellation policies than budget listings because preparation requires more effort and replacement bookings are typically much harder to realize on short notice.

With regard to the host's personal attributes, there do not occur any significant price effects due to the host's face visibility or gender. For the subset analysis of those hosts with visible faces (i.e., visible to Microsoft's API, n = 10,266), estimated age is positively associated with price, whereas degree of smile does not exhibit any significant effect (model VI). Moreover, whether or not a host manages more than one listing is associated with lower prices.

Overall, the regression models explain up to 39.6% of price variance. Control models based on the logarithm of price as a dependent variable yield similar results, where specifically none of the reported effects of the reputational attributes changes in sign or significance. The log(price) models yielded Adjusted R-squared values of up to 51.7%, an improvement that is in line with the observation of the skewed price distribution. We decided to retain the original (i.e., non-logarithmic) price data for the sake of higher coefficient interpretability.

Table 2. Regression results (OLS), *** p<.001; ** p<.01, * p<.05

		DV: price **(2 persons, 2 nights, including cleaning fee)**					
		(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**
Reputation Attributes	Average Rating Score (ARS)	18.575 *** (1.813)	14.831 *** (2.124)	13.870 *** (1.965)	13.331 *** (1.950)	12.509 *** (1.960)	10.786 *** (2.381)
	Number of Ratings (NoR)	-.360 *** (.025)	-1.624 *** (.374)	-1.840 *** (.346)	-1.895 *** (.344)	-1.851 *** (.344)	-2.149 *** (.417)
	ARS × NoR		.270 *** (.080)	.311 *** (.074)	.325 *** (.073)	.316 *** (.073)	.372 *** (.088)
	Membership	.494 *** (.043)	.493 *** (.043)	.426 *** (.040)	.357 *** (.040)	.388 *** (.041)	.371 *** (.049)
	Verified ID	2.283 (1.283)	2.302 (1.283)	-.958 (1.189)	-2.616 * (1.185)	-2.426 * (1.194)	-2.275 (1.419)
	Superhost Badge	1.557 (2.073)	-.051 (2.126)	3.627 (1.970)	3.513 (1.955)	3.715 (1.954)	2.255 (2.246)
	Number of Photos	1.055 *** (.075)	1.051 *** (.075)	1.110 *** (.069)	.982 *** (.070)	1.006 *** (.070)	1.102 *** (.083)
Apartment Attributes	Size	23.535 *** (.592)	23.574 *** (.592)	24.386 *** (.548)	23.606 *** (.546)	23.896 *** (.550)	24.409 *** (.661)
	Entire Home	42.954 *** (1.418)	42.976 *** (1.417)	44.782 *** (1.317)	41.446 *** (1.324)	40.967 *** (1.330)	38.489 *** (1.557)
	Distance to City Centre	-5.289 *** (.310)	-5.291 *** (.310)	-7.423 *** (.314)	-7.188 *** (.312)	-7.254 *** (.313)	-7.627 *** (.374)
City Attributes	Rent Price Level			10.318 *** (.233)	9.736 *** (.234)	9.712 *** (.234)	9.561 *** (.274)
	log(Population)			7.461 *** (.625)	5.932 *** (.629)	5.726 *** (.631)	6.615 *** (.766)
Convenience Attributes	Response Time ≤ 1h				-1.073 (1.309)	-.463 (1.317)	-.784 (1.541)
	Deposit required				16.426 *** (1.269)	16.174 *** (1.270)	17.126 *** (1.499)
	Check in/out comfort				-1.102 (1.358)	-1.209 (1.358)	-.109 (1.600)
	Minimum Stay				-.152 (.097)	-.140 (.097)	-.122 (.108)
	Instant Booking				2.179 (1.824)	2.663 (1.827)	-.569 (2.160)
	Cancellation Strictness				6.761 *** (.792)	6.903 *** (.793)	8.143 *** (.938)
Personal Attributes	Multiple Listings					-5.656 *** (1.479)	-6.322 *** (1.764)
	Gender (female)					2.116 (1.256)	1.005 (1.485)
	Photo: Face Visible					-.404 (1.319)	
	Age						.344 *** (.064)
	Degree of Smile						-1.051 (1.845)
	Intercept	-29.368 *** (8.802)	-11.712 (10.230)	-210.902 *** (12.363)	-184.324 *** (12.417)	-178.867 *** (12.558)	-193.906 *** (15.543)
N		13,884	13,884	13,884	13,884	13,884	10,266
Adj. R^2		.2796	.2801	.3839	.3956	.3962	.3955

Discussion

This paper was motivated by the importance of trust and reputation in sharing economy market places, and the fact that the providers of P2P products and services *personally* play a part in this game. Due to its' predominant popularity and importance, Airbnb was analyzed as a poster child example. By this, we extend the literature by important insights, including indication of a negative price effect of rating count, as well as an assessment of the specific monetization of star ratings. While a better average rating score (i.e., more stars) is reflected in a price markup, a more reliable rating (i.e., a higher number of ratings) is associated with a negative price impact. We acknowledge that hedonic price regressions encounter a methodological limit here as they assume a strict causal direction from the independent to the dependent variables. It is, however, very likely that the causal direction for ratings and prices (also) works in the opposite direction. Lower prices are likely to stimulate demand and hence yield more ratings. Moreover, a common cause to both lower prices and rating count may be rooted in low-budget accommodations in highly-frequented and hence competitive touristic areas. Also, for peer-to-peer accommodation sharing, a high number of ratings may be seen as an indication of a more impersonalized travel experience – thus even function as a negative price indicator.

Of course, in an economic setting where the consumers issue requests, high prices represent only one part of the picture and *demand* has to be taken into account too. In order to assess a host's economic success, prices would have to be weighted by the listing's utilization rate. This data, however, is harder, if not impossible, to obtain. The number of ratings (per given time interval), for instance may serve as a first proxy. This score, however, would be prone to the frequent phenomenon of long-term bookings (yielding high utilization yet low rating counts). Accessing a host's Airbnb calendar could be an alternative, but often days and weeks are blocked due personal usage or absences. Other options to approximate demand could draw upon click rates (which is not publicly provided by Airbnb), or the number of users that saved a listing to their wish list. Field experiments could represent another possibility. Edelman et al. (2017) conducted such an experiment analyzing the hosts' reactions to different guest characteristics on Airbnb, where mock profiles were used to issue requests. A similar approach may be conceivable for the host side, although much harder to realize. Ultimately, the platform operator's cooperation (e.g., the provision of anonymized transaction data) would be of great value to research (Parigi et al. 2017).

Another important aspect we would like to point to is the low variance within the distribution of average rating scores (see also Slee (2013) or Zervas et al. (2015) for discussions on that matter). Consistent with this observation, virtually all (i.e., 98.2%) average ratings from our dataset are either 5.0 (47.4%), 4.5 (43.9%), or 4.0 (6.9%) stars. This arguably impairs the informative power of such ratings. Even though the variation is subtle – there appears a measurable, consistent, and significant price effect due to differences in star rating. It appears that both hosts and guests on Airbnb have managed to interpret, value, and price star-rating-based reputation.

Prior research has found that hosts consciously increase prices once their rating score becomes visible for the first time (Gutt and Herrmann 2015).

Our findings have direct implications for hosts, guests, and platform providers. First, since a host's apartment properties can be assumed to be fixed, there is no claim to make that these parameters should or could be adapted in a favorable manner. Considering the reputation attributes, in contrast, hosts are able to lay the ground for price increases by improving their ratings, uploading additional (favorable) photos, and achieving a long-term membership of the platform. Insights from price regressions could provide pricing support to hosts, for instance, based on apartment properties, location, and season (i.e., demand and supply). In fact, Airbnb has recently introduced an automated pricing tool (Airbnb 2015).

Second, guests might benefit from the application of price regressions in decision support tools for optimal booking decisions. Such “smart booking” tools could be helpful for identifying particular over- or underpriced listings based on guests’ stated preferences. Furthermore, guests should be aware of their ability to significantly impact a host’s future economic fate through their rating. Therefore, guests should make use of their entitled power to rate hosts (either in a positive or negative direction) responsibly.

Third, for platform operators, our study provides indications of how to assist hosts in managing and presenting their listings. Specifically, as most platform operators’ business models work on provision basis, the results of our analysis indicate that they enable hosts to enforce justified price markups. This may include emphasizing positive ratings, long-term platform membership, and incentivizing the provision of a high number of expressive apartment photos.

Conclusion

In this paper, we considered the economic value of reputation in the sharing economy platform Airbnb. Our conceptual model suggests that reputation attributes significantly affect listing prices. Robust regression results confirm the majority of our hypotheses and quantify the corresponding economic values. We conclude that host reputation based on star ratings and the availability of apartment photos as signals are economically reflected in listing prices. These results have implications for all participating parties in P2P platforms: hosts, guests, and the platform providers. Nevertheless, reputation-based price effects require further investigation. The regression results provide useful insights for the case of Airbnb. Transferability to other sharing economy platforms is limited since type of resource, user motives, and reputation mechanisms may differ and moderate the price-determining processes. There exists, for instance, almost no personal interaction on platforms such as eBay or P2P car rental sites, potentially reducing the importance of a provider’s reputational capital for prices. In other domains such as ride sharing where there exist very high dependencies on the provider (e.g., on driving skills for obvious safety reasons), reputational capital may even more translate into economic capital than on Airbnb. This stresses the need for future research on the role of trust and reputation and its economic value on sharing economy platforms. Ultimately, the working principles of online reputation are greatly determined by their specific design, interfaces, and user representation. Practitioners and scholars of IS alike should be aware of potential economic and social impact design, code, and mechanism choices may exert down the line. Price analysis such as presented in this paper can thereby help to demonstrate and assess the economic value of IS itself. After all, it’s only “pixels, badges, and stars” (Teubner et al. 2016).

References

Aiken, K. D., and Boush, D. M. 2006. "Trustmarks, Objective-Source Ratings, and Implied Investments in Advertising: Investigating Online Trust and the Context-Specific Nature of Internet Signals," *Journal of the Academy of Marketing Science* (34:3), pp. 308–323.

Airbnb. 2014. "Superhost," (available at http://blog.airbnb.com/superhost/; retrieved February 10, 2017).

Airbnb. 2015. "Smart Pricing: Take the guesswork out of setting your price," (available at http://blog.airbnb.com/new-features-revealed-at-ao2015/; retrieved February 21, 2017).

Airbnb. 2017. "About us," (available at www.airbnb.com/about/about-us; retrieved February 15, 2017).

Basoglu, K. A., and Hess, T. J. 2014. "Online Business Reporting: A Signaling Theory Perspective," *Journal of Information Systems* (28:2), pp. 67–101.

Belk, R. 2010. "Sharing," *Journal of Consumer Research* (36:5), pp. 715–734.

Bente, G., Baptist, O., and Leuschner, H. 2012. "To buy or not to buy: Influence of seller photos and reputation on buyer trust and purchase behavior," *International Journal of Human Computer Studies* (70:1), pp. 1–13.

Berger, C. R., and Calabrese, R. J. 1975. "Some Explorations in Initial Interaction and Beyond: Toward a Developmental Theory of Interpersonal Communication," *Human Communication Research* (1:2), pp. 99–112.

Botsman, R., and Rogers, R. 2010. *What's Mine is Yours: How Collaborative Consumption is Changing the Way We Live*, Collins London.

Cheng, M. 2016. "Sharing economy: A review and agenda for future research," *International Journal of Hospitality Management* (57:2016), pp. 60–70.

Chevalier, J. A., and Mayzlin, D. 2006. "The effect of word of mouth on sales: Online book reviews," *Journal of Marketing Research* (43:3), pp. 345–354.

Duan, W., Gu, B., and Whinston, A. B. 2008. "Do online reviews matter?-An empirical investigation of panel data," *Decision Support Systems* (45:4), pp. 1007–1016.

Edelman, B. G., and Luca, M. 2014. "Digital Discrimination: The Case of Airbnb.com," *Harvard Business School Working Paper*.

Edelman, B. G., Luca, M., and Svirsky, D. 2017. "Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment," *American Economic Journal: Applied Economics (forthcoming)*.

Ert, E., Fleischer, A., and Magen, N. 2016. "Trust and Reputation in the Sharing Economy: The Role of Personal Photos on Airbnb," *Tourism Management* (55:2016), pp. 62–73.

Fagerstrøm, A., Pawar, S., Sigurdsson, V., Foxall, G. R., and Yani-de-Soriano, M. 2017. "That Personal Profile Image Might Jeopardize Your Rental Opportunity! On the Relative Impact of the Seller's Facial Expressions upon Buying Behavior on Airbnb," *Computers in Human Behavior (forthcoming)*.

Feickert, J. 2006. "Safeguarding Your Customers: The Guest's View of Hotel Security," *Cornell Hotel and Restaurant Administration Quarterly* (47:3), pp. 224–224.

Fradkin, A., Grewal, E., and Holtz, D., 2017. "The Determinants of Online Review Informativeness: Evidence from Field Experiments on Airbnb," *Working Paper*.

Fuller, M. A., Serva, M. A., and Benamati, J. 2007. "Seeing is believing: The transitory influence of reputation information on e-commerce trust and decision making," *Decision Sciences* (38:4), pp. 675–699.

Gebbia, J. 2016. "How Airbnb Designs for Trust," *TED.com*.

Guo, G., Zhang, J., Thalmann, D., Basu, A., and Yorke-Smith, N. 2014. "From Ratings to Trust: An Empirical Study of Implicit Trust in Recommender Systems," in *Symposium On Applied Computing*, pp. 248–253.

Gutt, D., and Herrmann, P. 2015. "Sharing Means Caring? Hosts' Price Reaction to Rating Visibility," in *ECIS 2015 Proceedings*, pp. 1–13.

Gutt, D., and Kundisch, D. 2016. "Money Talks (Even) in the Sharing Economy: Empirical Evidence for Price Effects in Online Ratings as Quality Signals," in *ICIS 2016 Proceedings*, pp. 1–10.

Guttentag, D. 2015. "Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector," *Current Issues in Tourism* (18:12), pp. 1192–1217.

Hawlitschek, F., Teubner, T., Adam, M. T. P., Borchers, N., Moehlmann, M., and Weinhardt, C. 2016. “Trust in the Sharing Economy: An Experimental Framework,” in *ICIS 2016 Proceedings*, pp. 1–14.

Hawlitschek, F., Teubner, T., and Gimpel, H. 2016. “Understanding the Sharing Economy—Drivers and Impediments for Participation in Peer-to-Peer Rental,” in *HICSS 2016 Proceedings*, pp. 4782–4791.

Hawlitschek, F., Teubner, T., and Weinhardt, C. 2016. “Trust in the Sharing Economy,” *Swiss Journal of Business Research and Practice* (70:1), pp. 26–44.

Huang, Q., Chen, X., Ou, C. X., Davison, R. M., and Hua, Z. 2017. “Understanding buyers’ loyalty to a C2C platform: the roles of social capital, satisfaction and perceived effectiveness of e-commerce institutional mechanisms,” *Information Systems Journal* (27:1), pp. 91–119.

Ikkala, T., and Lampinen, A. 2014. “Defining the Price of Hospitality: Networked Hospitality Exchange via Airbnb,” in *CSCW’14 Proceedings*, pp. 173–176.

Ikkala, T., and Lampinen, A. 2015. “Monetizing Network Hospitality: Hospitality and Sociability in the Context of Airbnb,” in *CSCW’15 Proceedings*, pp. 1033–1044.

Jiang, Z., and Benbasat, I. 2007. “Investigating the influence of the functional mechanisms of online product presentations,” *Information Systems Research* (18:4), pp. 454–470.

Jung, J., Yoon, S., Kim, S., Park, S., Lee, K., and Lee, U. 2016. “Social or Financial Goals? Comparative Analysis of User Behaviors in Couchsurfing and Airbnb,” *CHI’16 Proceedings*, pp. 2857–2863.

Kakar, V., Franco, J., Voelz, J., and Wu, J. 2016. “Effects of Host Race Information on Airbnb Listing Prices in San Francisco,” *Working Paper*.

Karlsson, L., Kemperman, A., and Dolnicar, S. 2017. “May I sleep in your bed? Getting permission to book,” *Annals of Tourism Research* (62:2017), pp. 1–12.

Ke, Q. 2017. “Sharing Means Renting?: An Entire-marketplace Analysis of Airbnb,” *Working Paper*.

Liang, L. J., Choi, H. C., and Joppe, M. 2016. “Understanding repurchase intention of Airbnb consumers: perceived authenticity, electronic word-of-mouth, and price sensitivity,” Journal of Travel & Tourism Marketing, pp. 1–17.

Liang, S., Schuckert, M., Law, R., and Chen, C.-C. 2017. “Be a ‘Superhost’: The importance of badge systems for peer-to-peer rental accommodations,” *Tourism Management* (60:2017), pp. 454–465.

Luca, M. 2016. “Reviews, reputation, and revenue: The case of Yelp.com,” *Working Paper*.

Ma, X., Hancock, J. T., Mingjie, K. L., and Naaman, M. 2017. “Self-Disclosure and Perceived Trustworthiness of Airbnb Host Profiles,” in *CSCW’17 Proceedings*, pp. 1–13.

Möhlmann, M. 2015. “Collaborative Consumption: Determinants of Satisfaction and the Likelihood of Using a Sharing Economy Option Again,” Journal of Consumer Behaviour, (14:3), pp. 193–207.

Mulshine, M. 2015. “After a disappointing Airbnb stay, I realized there’s a major flaw in the review system,” *Business Insider* (available at http://www.businessinsider.com/why-airbnb-reviews-are-a-problem-for-the-site-2015-6?IR=T; retrieved January 19, 2017).

Nahapiet, J., and Ghoshal, S. 1998. “Social Capital, Intellectual Capital, and the Organizational Advantage,” *Academy of Management Review* (23:2), pp. 242–266.

Norcie, G., De Cristofaro, E., and Bellotti, V. 2013. “Bootstrapping trust in online dating: Social verification of online dating profiles,” in *International Conference on Financial Cryptography and Data Security*, pp. 149–163.

Orlowski, J., and Wicker, P. 2015. “The monetary value of social capital,” *Journal of Behavioral and Experimental Economics* (57:2015), pp. 26–36.

Pan, Y., and Jackson, R. T. 2008. “Ethnic difference in the relationship between acute inflammation and serum ferritin in US adult males,” *Epidemiology and Infection* (136:3), pp. 421–431.

Parigi, P., Santana, J. J., and Cook, K. S. 2017. “Online Field Experiments: Studying Social Interactions in Context,” *Social Psychology Quarterly (forthcoming)*.

PwC. 2015. “The Sharing Economy - Consumer Intelligence Series,” PricewaterhouseCoopers, pp. 1–30.

Resnick, P., and Zeckhauser, R. 2002. "Trust among strangers in internet transactions: Empirical analysis of eBay's reputation system," *Advances in Applied Microeconomics Working Paper*.

Rosen, S. 1974. "Hedonic prices and implicit markets: product differentiation in pure competition," *Journal of Political Economy* (82:1), pp. 34–55.

Rousseau, D. M., Sitkin, S. B., Burt, R. S., and Camerer, C. 1998. "Not so different after all: A cross-discipline view of trust," *Academy of Management Review* (23:3), pp. 393–404.

Schor, J. 2016. "Debating the Sharing Economy," *Journal of Self-Governance and Management Economics* (4:3), pp. 7–22.

Slee, T. 2013. "Some Obvious Things About Internet Reputation Systems," *Working Paper*, pp. 1–13.

Spence, M. 2002. "Signaling in Retrospect and the Informational Structure of Markets," *The American Economic Review* (92:3), pp. 434–459.

Strader, T. J., and Ramaswami, S. N. 2002. "The value of seller trustworthiness in C2C online markets," *Communications of the ACM* (45:12), pp. 45–49.

Sundararajan, A. 2014. "Peer-to-peer businesses and the sharing (collaborative) economy: Overview, economic effects and regulatory issues," *Written testimony for the hearing titled 'The Power of Connection: Peer to Peer Businesses.'*

Sundararajan, A. 2016. *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism*, MIT Press.

Teubner, T. 2014. "Thoughts on the Sharing Economy," in *Proceedings of the International Conference on e-Commerce*, pp. 322–326.

Teubner, T., Adam, M. T. P., Camacho, S., and Hassanein, K. 2014. "Understanding resource sharing in C2C platforms: The role of picture humanization," in *ACIS 2014 Proceedings*, pp. 1–10.

Teubner, T., Saade, N., Hawlitschek, F., and Weinhardt, C. 2016. "It's only Pixels, Badges, and Stars: On the Economic Value of Reputation on Airbnb," in *ACIS 2016 Proceedings*, pp. 1–11.

Wang, D., and Nicolau, J. L. 2017. "Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com," *International Journal of Hospitality Management* (62:2017), pp. 120–131.

Xiong, L., and Liu, L. 2004. "Peertrust: Supporting reputation-based trust for peer-to-peer electronic communities," *IEEE Transactions on Knowledge and Data Engineering* (16:7), pp. 843–857.

Zervas, G., Proserpio, D., and Byers, J. 2015. "A first look at online reputation on Airbnb, where every stay is above average," *SSRN Working Paper 2554500*.

Zhang, S., Lee, D., Singh, P., and Srinivasan, K. 2016. "How Much Is An Image Worth? An Empirical Analysis of Property's Image Aesthetic Quality on Demand at Airbnb," in *ICIS 2016 Proceedings*, pp. 1–20.

Appendix

Table A1. *Correlation matrix (Pearson correlation coefficients; Significance levels: *** p<.001; ** p<.01, * p<.05)*

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1) Price	.057***	-.051	.001	.029***	.234***	.135***	.417***	.372***	-.116	.271***	.098***	-.016	.262***	.032***	.040***	-.006	.200***	-.011	-.018	.018*
(2) Average Rating Score		.025**	.277***	.059***	.096***	-.027	-.081	-.017	-.005	-.003	-.004	-.004	.031***	.033***	.011	-.074	-.005	.049***	.064***	-.135
(3) Number of Ratings			.158***	.045***	.190***	.296***	.026**	-.028	-.079	-.003	.049***	.180***	-.006	.057***	.014	.149***	.083***	-.055	-.006	.112***
(4) Superhost				.064***	.110***	.018*	-.044	-.057	-.026	-.026	-.054	.084***	-.004	.027**	.013	.003	.011	-.013	.042***	.007
(5) ID verified					.105***	.036***	.008	-.012	-.011	.047***	.034***	.073***	.085***	.046***	.006	.027**	.088***	-.119	.067***	.004
(6) Number of Photos						.247***	.228***	.169***	.001	-.026	.057***	.122***	.154***	.066***	.086***	.107***	.172***	-.046	.005	.155***
(7) Membership							.110***	.088***	-.002	-.010	.153***	.006	.117***	.000	.115***	-.001	.181***	-.025	-.023	.232***
(8) Size								.343***	.014	-.047	.017*	.034***	.125***	.006	.030***	.048***	.152***	-.047	-.047	.157***
(9) Entire home									-.020	-.065	.062***	.004	.192***	.034***	.097***	.028***	.144***	-.011	-.041	-.015
(10) Distance to City Center										.045***	.399***	-.011	.026**	-.014	.060***	.023**	.006	.049***	-.003	-.070
(11) Rent Price Level											.160***	-.058	.153***	.026**	-.028	-.054	.063***	-.007	.023**	-.068
(12) *log*(Population)												-.050	.183***	.029***	.103***	-.009	.117***	.003	-.025	-.089
(13) Response time < 1 hour													-.021	.038***	-.023	.358***	.033***	-.090	.021*	.143***
(14) Requires Deposit														.082***	.093***	-.021	.207***	.011	-.012	-.026
(15) Check in/out Comfort															.035***	.014	.115***	-.029	-.006	-.024
(16) Minimum Stay																.002	.081***	-.010	.006	.034***
(17) Instant Booking																	.015	-.062	.003	.120***
(18) Cancellation Strictness Level																		-.034	-.039	.084***
(19) Gender: Female																			-.033	-.048
(20) Photo: Face visible																				-.054
(21) Multiple Listings																				