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It's only pixels, badges, and stars: On the economic value of reputation on Airbnb

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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 host 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. In this paper, we thus consider the economic value of trust artefacts on Airbnb by quantifying price effects of common reputation features from a signalling theory perspective. Our analysis is based on a large-scale dataset from 86 German cities and hedonic price modelling. We find that index signals such as the hosts' rating scores, duration of membership, and Superhost status provide 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 IS artefacts intended to facilitate peer-to-peer platform interactions.

Keywords Airbnb, Trust, Reputation, Sharing Economy, Peer-to-Peer Platforms, Signalling Theory, Hedonic Price Models

1 Introduction

The worldwide economic importance of the sharing economy has grown rapidly over the last decade (Sundararajan, 2014; Teubner & Hawlitschek, 2016). Peer-to-peer (P2P) platforms in the sharing economy allow users to offer products and services while the platform operator manages and maintains the marketplace (Botsman & Rogers, 2010). Platforms for P2P accommodation sharing have experienced particular strong growth (Pizam, 2014) and represent an important sub-domain within the broader sharing economy landscape. One of the most popular and frequently discussed examples for this phenomenon is Airbnb (Guttentag, 2015), with currently over 2 million offers in 192 countries worldwide, facilitating an average of 500,000 stays per night.[1] Since its foundation in 2008, Airbnb has been used by over 50 million guests.[2] Similar accommodation sharing services are offered by Flipkey, Homeaway, Roomora, Wimdu, and 9Flats.

In contrast to the traditional hotel industry, platforms like 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 potential 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 et al., 2016a). Therefore a host's overall appearance, including profile and product pictures or information on the hosting track record, is critical (Ert et al., 2016). Since the entire process of exploring and booking is conducted online, the elements displayed by 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. The financial success of Airbnb 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. Within the scope of this paper, we thus address the following research question: *How do different UI artifacts of the Airbnb reputation system translate into economic value?*

Trust is a complex construct, which has received much attention from various research domains, 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. For this research, trust is conceptualized as an Airbnb user's willingness to rely on a host's actions and intension, which can be further separated into the categories of ability, integrity, and benevolence (Hawlitschek et al., 2016). Reputation on the platform, in this sense, captures a host's tangible record of prior host-guest interactions. With this work, we contribute to existing research 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, duration of membership, and Airbnb's Superhost badge are reflected in price mark-ups. The remainder of this paper is organized as follows. In Sections 2 and 3, we review related literature 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.

2 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 particular important to the sharing economy and especially to P2P markets (Botsman & Rogers, 2010; Hawlitschek et al., 2016a; Hawlitschek et al., 2016c; Belk, 2010; Strader & Ramaswami, 2002). Consequently, P2P platform operators have implemented mechanisms and signals to facilitate trust-building between providers and consumers (Resnick & Zeckhauser, 2002), including identity verification, mutual rating and review schemes, insurances, and specific web design techniques (Teubner, 2014; Gebbia, 2016). Reputation and electronic word of mouth thereby help to assess the trustworthiness of peers in electronic communities (Xiong & Liu, 2004). Compared to traditional e-commerce where an impeccable

[1] http://expandedramblings.com/index.php/airbnb-statistics/

[2] http://blog.airbnb.com/wp-content/uploads/2015/09/Airbnb-Summer-Travel-Report-1.pdf

reputation can lead to an increase in product sales, that is, in volume (Chevalier & 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 might not be reflected in additional sales, but rather in higher listing prices. Related research provides support for this assumption, showing that hosts on Airbnb capitalize high reputation either by choosing guests more selectively or demanding higher prices (Gutt & Herrmann, 2015; Ikkala & Lampinen, 2015).

Several recent studies have set out to further explore prices and pricing decisions on Airbnb. Edelman and Luca (2014), for instance, 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 percent. 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 favour of the existence of racial discrimination on Airbnb (Edelman et al., 2016). 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, they 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. [3] Moreover, Ikkala and 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 and Herrmann (2015) considered the effect of rating score availability. Based on 14,000 listings, they analysed 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 reviews. Here, hosts were found to monetize rating availability by a mark-up of €2.69.

Besides such direct trust scores, user representation is also considered important (Teubner et al., 2014) Ert et al. (2016), for instance, 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 AMT 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.

Slee (2013) as well as Zervas et al. (2015) pointed out a marked property of Airbnb's 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 percent of Airbnb's listings (Zervas et al., 2015) and virtually all of the rated BlaBlaCar rides exhibit 4.5 or 5-star scores, implying little discriminating power of star ratings. Fradkin et al. (2014) 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.

This 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 reviews, 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 short-term equilibrium where hosts set individual prices exactly as high as they can – based on their own and their listing's properties. 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 creates an ideal environment for competition and price discovery processes. Second, sharing economy interactions are conducted on a personal, that is, non-professional basis. And indeed, the lines between private and professional spheres are blurring,

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

where today many services are not only provided by corporate institutions, but increasingly by individuals (Teubner & Hawlitschek, 2016). This makes personal attributes, such as hosts' reputation scores, more salient, since conventional branding does not apply. 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, platform-specific template and contain the same informational bits and pieces. This structure renders the effects of investigated factors highly comparable across large data sets of accommodations and hosts.

3 Research Model & Hypotheses Development

In order to investigate the price effects of different trust artefacts on Airbnb, we propose the research model presented in Figure 1. Our reasoning is based on signaling theory which we outline in greater detail in the following.

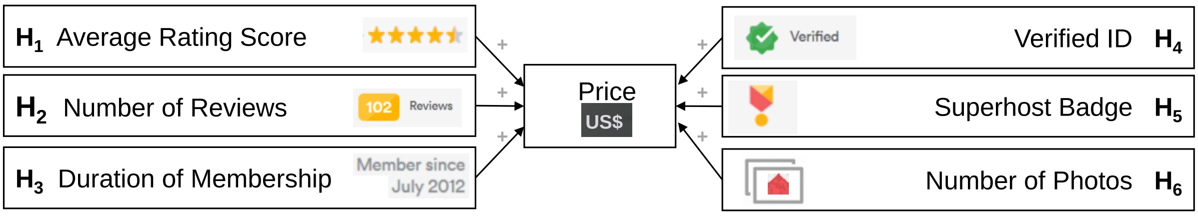

Figure 1: Research model

Signaling theory focuses on asymmetries of information between 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 & Hess, 2014). Signals can be classified as assessment and conventional signals (Shami et al., 2009), where assessment signals are considered more reliable, as they are either associated with effort/cost for the signaler (e.g., a well-crafted CV; handicap signal), or rely on some form of confirmation through an independent third party (index signal). Conventional signals such as simple self-descriptions, promises, etc., in contrast, are less reliable, as they are easy to create and let room for deception. All signals considered here represent assessment signals, as they are either associated with effort or based on external evaluation. Rating schemes (including average rating score and number of reviews) 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 & Zeckhauser, 2002).

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

User ratings were commonly found to establish trust between peers (Jøsang & Boyd, 2007; Fuller et al., 2007; Bente et al., 2012). Moreover, empirical evidence suggests that different levels of reputation, based on rating scores, translate into different prices (Edelman & Luca, 2014). For Airbnb, the authors analysed the star rating's different sub-categories, 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. 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) 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 & Mayzlin, 2006; Luca, 2011). 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 signalling theory suggest that a higher rating count renders average scores more reliable, hence more trustworthy, since a low number of reviews may be acquired by friends and family and is naturally more prone to outliers. Moreover, a high number of ratings points to consistency and experience as a host. Empirical evidence on this matter is sparse. Ert et al. (2015), for instance, do not find any significant price effects on Airbnb based on the number of reviews. Their analysis, however, is only based on 175 listings from Sweden, which may be a too small dataset to draw reliable conclusions from. Duan et al. (2008), 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.*

3.2 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 (Hawlitschek and Lippert, 2015). 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 an account 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:

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 behaviours (self-commitment). User verification was found to increase trust, for instance for the case of online dating (Norcie et al., 2013). The importance of genuine and reliable online identities is also illustrated by the efforts taken by platforms like Ebay to avoid users create multiple, potentially mal-intended accounts (Resnick and Zeckhauser, 2002). We suggest that the trust effect of ID verification can be commercialized in Airbnb too:

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

3.3 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 [4]. 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. Analogous to our reasoning above, we suggest that hosts utilize this capital for price premiums. 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. 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 hypothesise:

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

[4] For details, see `www.airbnb.com/superhost`

4 Airbnb Data Analysis

Our analysis is based on a dataset of 13,884 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. Second, we combine and enrich this data with information from other sources such as Google's API, 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 centre," as a proxy of how well a certain apartment is located within a city. We excluded listings with a rating count smaller than three, for which Airbnb does not provide any star rating. Additionally, in order to increase the comparability among considered listings, we decided to exclude the few accommodations with more than six guests (i.e., hostels, hotels, and large-scale dormitories). For each listing, we recorded attributes from the following categories: i) trust & reputation, ii) city, iii) personal, iv) convenience, and v) apartment.

Trust & reputation attributes: This category contains the focus variables of this study, including Average Rating Score, #Reviews, ID Verification, Duration of Membership, as well as Superhost Badge, and #Apartment Photos.

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. Moreover, users on Airbnb offer different types of accommodations, including shared rooms (i.e., the couch in the living room), private rooms (i.e., guest room), and entire apartment. Besides these aspects, the value of real estate strongly depends on location. Hence, we included the listing's distance to the city centre as a control variable. Since this data is provided as latitude/longitude coordinates, it is computed using the haversine formula.[5]

City attributes: This category contains the factors Rent Price, indicating the average rent price level of a given city (€/m²; as provided by wohnungsboerse.net)[6], as well as the log of population (in million inhabitants; as provided by Wikipedia).

Personal attributes: Airbnb prominently displays the hosts' first names. We used this surname to compute indicator variables for gender and for whether the host appears as single person or as a couple. For the gender variable, we utilized the Python library *SexMachine,*[7] which yielded scores between 0 and 1, reflecting the probability that a given surname belongs to a male/female person. The couple dummy was based on whether the host name included indicators such as "and" or the ampersand sign.

Convenience attributes: This category includes options the host does or does not offer for the guest's convenience. This includes instant booking, deposit requirement, charging of cleaning fee, cancellation strictness, as well as the minimum possible duration of a stay. Moreover, some host allow for early check-in/ late check-out. Furthermore, this category includes the host's response rate and response time.

4.1 Data set and Airbnb characteristics

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 reviews, duration of membership, and number of photos. Overall, 11.6% of the listings are offered by users with Superhost status, 58.6% by those with verified ID, and 47.4% by male users. A minority of 3.7% appears as a couple. Furthermore, 13.5% of the listings can be rented via instant booking; 64.7% charge a separate cleaning fee (US$ 30 on average), 38.4% a security deposit (US$ 270 on average).

[5] The haversine formula is used to calculate the distance between two points on a sphere.
[6] Wohnungsboerse.net is a German platform for real estate brokerage.
[7] `https://github.com/ferhatelmas/sexmachine`

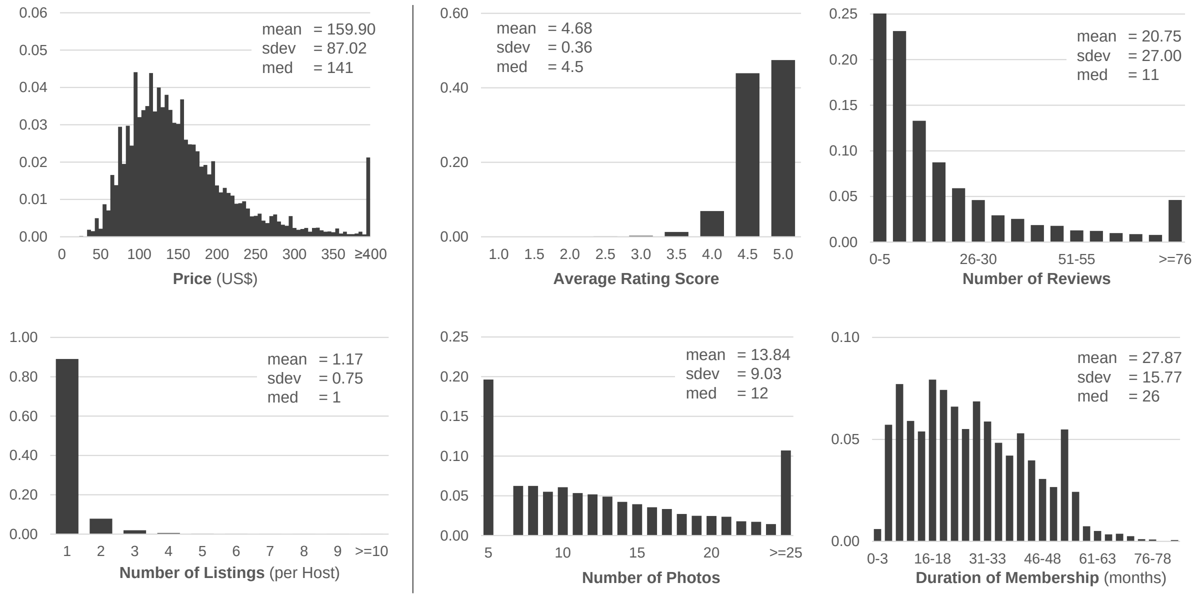

Figure 2: Distributions of main variables (including mean, standard deviation, and median)

4.2 Hedonic price regression

To assess the attributes' economic value, we conducted a set of linear regressions. 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 (Rosen, 1974; Ert et al., 2016), 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 independent variables. The fundamental apartment properties are used as a core set of independent variables for all regressions. Table 1 shows the results of the main regressions I through IV with price (2 persons, 2 nights, including cleaning fee) as dependent and the above stated factors as independent variables.

The results reveal a significant positive effect of almost all trust and reputation related attributes. More specifically, an increase by one star in the rating score is associated with a price increase of US$ 8.91. In addition, we find a positive effect of the Superhost badge, increasing listing prices by US$ 2.974. Also, duration of membership drives listing prices by US$ .20 per month. In contrast, the effect of ID verification appears to be unstable and depending on the set of included control variables, ranging from significantly positive (I) to significantly negative values (IV). The results also confirm the negative price impact of review count. Each additional review is associated with a price delta of US$ .20.

	DV: price (2 persons, 2 nights, including cleaning fee)			
	(I)	**(II)**	**(III)**	**(IV)**
Average Rating Score	10.156***	9.955***	9.832***	8.908***
	(-1.028)	(.956)	(.958)	(.914)
Number of Reviews	−.210***	−.223***	−.221***	−.204***
	(.014)	(.013)	(.013)	(.013)
Superhost Badge	.634	2.929**	3.012**	2.974**
	(-1.175)	(-1.095)	(-1.095)	(-1.043)
Verified ID	1.611*	−.178	.084	−2.106**
	(.728)	(.678)	(.682)	(.652)
Duration Membership	.310***	.268***	.269***	.203***
	(.024)	(.023)	(.023)	(.022)
Number of Photos	.718***	.732***	.737***	.555***
	(.043)	(.040)	(.040)	(.038)
Apartment Attributes	yes	yes	yes	yes
City Attributes	-	yes	yes	yes
Personal Attributes	-	-	yes	yes
Convenience Attributes	-	-	-	yes
Number of observations	13,884			
Adj. R^2	.310	.403	.404	.463

*Table 1. Regression results (OLS regressions), *** p<.001; ** p<.01, * p<.05*

Our results suggest that the trust and reputation attributes employed by Airbnb constitute significant economic value. As we hypothesized, average rating score (H_1), duration of membership (H_3), Superhost status (H_5), and photos (H_6) are positively associated with listing price. We did not find a consistent effect of ID verification (H_4). In contrast to our hypothesis, a high number of reviews is negatively associated with price (H_2).

The examination of the other attribute categories reveals, quite expectedly, that entire homes are on average more expansive than private rooms or shared apartments. Also, larger apartments are more expensive. There does not occur any significant price effect due to gender or the couple dummy. Distance to city centre is significantly reflected in prices ($b_{(IV)}$=-5.114, p<.001). Overall, the regressions explain up to 46.3% of price variance, which can be considered a reasonable fraction, keeping in mind that the variety of offered accommodations on Airbnb is large, including castles, tree houses, and boats. Moreover, this degree of explanatory power is comparable with prior work (44% to 47%, Ert et al., 2016; Edelman and Luca (2014) do not provide R-squared values).

5 Discussion

This paper was motivated by the important role of trust and reputation in sharing economy market places, and the fact that the providers of P2P products and services *personally* play a crucial role in this game. Due to its' predominant popularity and importance, Airbnb was analysed as a poster child example. To the best of our knowledge, this paper is the first to investigate the associations of the great majority of all visible attributes on Airbnb with listing prices in Germany within an integrated model. It is also the first to quantify the economic value of different trust-related UI artifacts and measures. By this, we extend the literature by important insights, including indication of a negative price effect of review count, as well as an assessment of how much specifically star ratings can be monetized. Even though this finding appears counter-intuitive, experimental research on user-generated ratings has come to similar results, indicating that "ratings are positively associated with perceptions of product quality and purchase intention, but that people attend to average product ratings, but not to the number of ratings or to the combination of the average and the number of ratings together" (Flanagin et al., 2014). The causal direction for reviews and prices may, however, work in the opposite direction. Lower prices are likely to stimulate demand and hence yield more reviews. Moreover, there may be a common cause to both lower prices and review count. Low-budget accommodations in highly-frequented and hence competitive touristic areas, for instance, can be expected to yield both low prices *and* a high number of (short-term) bookings. Also, in the domain of accommodation, a high number of ratings is likely to be associated with a more impersonalized travel experience. Airbnb users, however, might seek such personalized social experiences (Hawlitschek et al., 2016b). The impression of an apartment with a high number of ratings may be rather that of an anonymous hotel.

Of course, in an economic setting where the demand side issues requests, high prices represent only one part of the picture and *demand* would have to be taken into account, too. In order to assess a host's economic success, prices would have to be weighted by an apartment's utilization rate. This data, however, is harder, if not impossible, to obtain. The number of reviews (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 review counts). Accessing a host's Airbnb calendar could be an alternative, but often periods are blocked, not due to guest accommodation but for private reasons or absences. In this sense, prohibitively high prices are certainly over-interpreted by hedonic models. Other options to approximate demand could use click rates (which is not publicly provided by Airbnb), or how many people have saved a listing to their wishlist. Field experiments could represent an elegant, though expensive, way out. Edelman et al. (2016) conducted such an experiment for the guest perspective on Airbnb, where mock profiles were used to issue mock requests. User names were varied while all other factors were held constant. A similar approach is conceivable for the host side. Mock host profiles with varying duration of membership, average ratings, etc. are, however, much harder to create.

Another important aspect we would like to point to is the low degree of variance within the distribution of average rating scores (see also Slee (2013) or Zervas et al. (2015) for discussions on that matter). Consistent with such common observations, 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. Our analysis, however, revealed that – even though the variation is subtle – there appears a measurable, consistent, and significant price effect.

The obvious price impact of Airbnb's trust attributes points to several perspectives of complementary and future analysis. First, the observation of a correlation between peer-generated ratings and prices is in line with findings from traditional markets (Yacouel & Fleischer, 2012). Prior research has also found that hosts consciously increase prices once their rating score becomes visible for the first time (Gutt & Herrmann, 2015). Picking up this line, our research further differentiates the effect of rating vs. no rating towards the impact single stars. Although the rating itself has a positive impact, we observe a negative effect for the rating count. From a signalling and social proof theory perspective, this appears counter-intuitive since a larger number of handled guests speaks in favour of good quality. Such hosts can be expected to be well-experienced, and many prior guests have chosen to rely on their value proposition. With regard to the non-robustness of ID verification, it might be that its effect is perishing due to the large number of other, potentially more salient trust-related UI artifacts and measures on Airbnb.

Our findings also pose the question which implications the results have for hosts, guests and P2P platform providers. Hosts dispose of an apartment of given size and location. Consequently, we assume that apartment and city properties are exogenous. Considering trust and convenience properties, in contrast, hosts are able to lay the ground for price increases by the (endogenous) factor of uploaded photos. For index signals such as positive reviews, hosts will in fact have to provide a good service, or rely on dubious means such as fake transactions. For platform operators, price regressions may serve as an anchor for user guidance. Airbnb could and does already provide pricing support, based on apartment properties, location, and season. Also for guests, such tools could be helpful for identifying particular over- or under-priced listings.

One major limitation of hedonic price models using empirical data, after all, lies in the impossibility of causal statements. As we have mentioned above, certain factors may not necessarily drive prices, but quite to the opposite, be determined by price. Also, many factors and price may have common causes. Our hypotheses are accordingly written out in a precautious way, using *associations* rather than cause-and-effect statements. Price enforceability (i.e., requests or utilization) would have to be taken into account to resolve this issue, requiring detailed, intimate, and long-term insights into Airbnb hosts' profiles. Such insights, however, would depend on insights into Airbnb's internal transaction data (which we do not have). To begin with, additional control variables could further improve explanatory power of current, although problematic, hedonic price models. Ert et al. (2016), for example, analysed the role of personal photos on Airbnb. Specifically, they considered a user's trustworthiness and attractiveness as conveyed by the profile photo. Such facial information could be assessed on a large-scale basis by algorithmic approaches, for instance using Microsoft's Face and Emotions API.[8] Moreover, sentiment analysis on written user reviews could enhance price models.

6 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 hypothesis and quantify the corresponding economic values. Interestingly, ID verification did not show a consistent price effect and (counterintuitively) review count was negatively associated with price. We conclude that host reputation does economically reflect in listing prices. These results have implications for all participating parties in P2P platforms, hosts, guests, and the platform operator, that is.

Nevertheless, reputation-based price effects require further investigation. The regression results provide useful insights for the case of Airbnb. Their implications with respect to other sharing economy platforms may still be limited since user motives and trust-building mechanisms may differ greatly. There exists, for instance, almost no personal interaction on platforms such as Ebay or the P2P car rental platform Drivy, potentially rendering a provider's reputational capital less important. Moreover, on these platforms, product variety is lower and comparability is higher, potentially rendering product specificities more prevalent, as compared to Airbnb. This stresses the need for future (IS) research on the role of trust and reputation and its economic value on sharing economy platforms in relation to other potential motives, drivers, and impediments. Ultimately, since the working principles of online reputation mechanisms are greatly determined by their specific design, including interfaces etc., price analysis such as presented in this paper can help to assess and increase the economic value of IS itself.

[8] `https://www.microsoft.com/cognitive-services/en-us/emotion-api`

7 References

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