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A HOMEOWNER’S GUIDE TO AIRBNB: THEORY AND EMPIRICAL EVIDENCE FOR OPTIMAL PRICING CONDITIONAL ON ONLINE RATINGS

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A HOMEOWNER’S GUIDE TO AIRBNB: THEORY AND EMPIRICAL EVIDENCE FOR OPTIMAL PRICING CONDITIONAL ON ONLINE RATINGS

Research paper

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Abstract

Optimal price setting in peer-to-peer markets featuring online ratings requires incorporating interactions between prices and ratings. Additionally, recent literature reports that online ratings in peer-to-peer markets tend to be inflated overall, undermining the reliability of online ratings as a quality signal. This study proposes a two-period model for optimal price setting that takes (potentially inflated) ratings into account. Our theoretical findings suggest that sellers in the medium-quality segment have an incentive to lower first-period prices to monetize on increased second-period ratings and that the possibility on monetizing on second-period ratings depends on the reliability of the rating system. Additionally, we find that total profits and prices increase with online ratings and additional quality signals. Empirically, conducting Difference-in-Difference regressions on a comprehensive panel data set from Airbnb, we can validate that price increases lead to lower ratings, and we find empirical support for the prediction that additional quality signals increase prices. Our work comes with substantial implications for sellers in peer-to-peer markets looking for an optimal price setting strategy. Moreover, we argue that our theoretical finding on the weights between online ratings and additional quality signals translates to conventional online markets.

Keywords: Sharing Economy, Online Ratings, Optimal Price Setting, DiD-Regression.

1 Introduction

Peer-to-peer markets such as Airbnb, Uber, and Homeaway have witnessed unprecedented economic growth over the past few years. On Airbnb alone, a peer-to-peer marketplace in which homeowners can rent out their unused space to potential guests, 640,000 unique hosts offer a total number of 2.3 million listings with an average of 500,000 stays per night in 57,000 different available cities and 191 different countries.2 A key feature of these peer-to-peer marketplaces is that, in the case of Airbnb, private homeowners take on the role of micro-entrepreneurs. To tap this substantial stream of additional financial income, hosts have to make managerial decisions on a daily basis; they must manage booking requests, provide information on their rented property, and set prices. These managerial tasks are nontrivial for professional hotel chains, but they are even more so for hosts on sharing platforms.

From an academic point of view, research on price setting strategies has a long-standing tradition in the economics (e.g., Nagle 1984, Stigler 1961) and marketing (e.g., Tellis 1986) literature. With the advent of online reviews and social networks, theoretical and empirical analyses of price setting strategies have drawn significant interest from the information systems literature (e.g., Ajrloiu et al. 2016, Cabral and Hortacsu 2010). However, research on price setting in peer-to-peer markets has only recently begun to emerge. From a practical point of view, setting the right price for an Airbnb listing can be very

1 This work was partially supported by the German Research Foundation (DFG) within the Collaborative Research Centre “On-the-Fly Computing” (SFB 901).
challenging. For instance, it is unclear how to set initial prices for a newly offered listing. Furthermore, once a host has accommodated a couple of guests, it is unclear how to adjust prices without suffering a loss of profit. Conducting a Google search with the search string “how to set prices on Airbnb” yields a multitude of results based mostly on anecdotal gut feelings or the usage of automated pricing tools (3.21 million results as of November 29, 2016). This underlines a lack of theoretical understanding and a need for academic research with substantial practical implications. Taking into account the quality features of a listing (for example, the location, the number of guests that can be accommodated, a detailed description about the property, or the online rating score), hosts seeking to explore the additional income opportunity of their space to the fullest need to find a profit-maximizing price. Ultimately, the motivation to act as a host in the sharing economy can be socially as well as financially motivated; given the number of hosts with multiple listings, it seems evident that a substantial number of hosts are financially motivated (Gutt and Herrmann 2015).

Additionally, websites like Airbnb operate an online rating system to erode the potentially large information asymmetry between hosts and guests to establish trust between these two parties (Fradkin et al. 2015, Teubner et al. 2016). Potential guests in general can use (i) online reviews or (ii) additional quality signals (such as badges or number of reviews) to learn about the host and her accommodation, and it seems reasonable that this knowledge cannot be obtained through other ways. With respect to price setting, the interactions between online ratings and prices need to be taken into account because empirical evidence suggests that online ratings can significantly influence prices (Proserpio et al. 2016, Teubner et al. 2016). For example, high ratings can be a good signal of quality that enables a host to ask for higher prices. However, in turn, higher prices might lead to lower ratings and thus, hosts might price strategically to establish a good online rating and subsequently raise prices to leverage their ratings. Although optimal price setting taking into account interactions with online ratings has been investigated for conventional e-commerce markets (Li and Hitt 2010), this topic has been widely neglected for the peer-to-peer markets of the sharing economy.

Setting profit-maximizing prices that take ratings into account, however, is significantly obstructed by the conjecture that online ratings in peer-to-peer platforms are inflated (Zervas et al. 2015). Online ratings are a key mechanism to erode information asymmetry between buyers and sellers, yet the rating scores (commonly on a scale from one to five) are reported to be implausibly high (inflated) across a majority of listings. Rating inflation undermines the function of online ratings as a quality signal for hosts and can be, for instance, due to the bilateral rating systems (Fradkin et al. 2015), the high costs of leaving a bad review (Horton and Golden 2015), a general underreporting bias (Dellarocas and Wood 2008), or the social interaction between hosts and guests (Zervas et al. 2015). Also, besides publicly visible online ratings, Airbnb offers a private feedback channel to the host, where negative feedback that might be expressed online and affect ratings could instead be reflected in the private channel (Fradkin et al. 2015). Due to supposedly inflated online rating scores, additional quality signals—including verified IDs, the sheer number of reviews, a so-called superhost status, and photos—can be an important supplemental way to convey the quality of a property to potential guests.

Consequently, this study aims to extend and test the theory on profit-maximizing prices, taking into account inflated online ratings, additional quality signals, and interactions between prices and online ratings. Thus, in our work we pose the following research question:

*How do you set profit-maximizing prices on platforms that account for interactions between prices and online ratings under rating inflation and additional quality signals?*

Therefore, this study proposes a theoretical model that accommodates for inflated online ratings and additional quality signals to obtain profit-maximizing prices in a two-period model. First, as our theoretical findings, we delineate several model predictions on profit-maximizing price setting. Second, from our model predictions, we derive testable hypotheses to empirically validate our model using a comprehensive panel data set on Airbnb, collected between July 12, 2016, and October 11, 2016, for eight major U.S. cities using a customized web crawler. This data allows us to observe historical data on prices and ratings. In summary, we theoretically find that (i) sellers with neither too high nor too low
quality have an incentive to lower first-period prices to monetize on increased second-period ratings, (ii) the possibility on monetizing on second-period ratings depends on the reliability of the rating system, (iii) total profits increase in additional quality signals when buyers consider both ratings and additional quality signals, and (iv) second-period prices increase with perceived quality and with additional quality signals. Empirically, we can (i) validate the key assumption of our model that price increases lead to lower ratings and (ii) validate our model in that we find evidence to support the claim that prices increase with increasing additional quality signals (based on our operationalization).

Our work thus makes several substantial theoretical and empirical contributions to the literature and comes with important implications to buyers and sellers in peer-to-peer markets. First, and to the best of our knowledge, we are the first to analyze optimal price setting conditional on price-rating interactions for the sharing economy, where online ratings tend to be inflated and additional quality signals play a role. In this way, we contribute to the growing literature on the sharing economy and focus on a special feature of the sharing economy that was not analyzed in previous studies. The theoretical results are highly relevant for sellers in sharing markets that feature online ratings, in that our predictions can guide a homeowner’s optimal price setting, which merely requires knowledge of the homeowner’s own (perceived) quality. Second, our robust panel data analysis reveals that price increases decrease online ratings and that sellers in fact command higher prices when they accumulate quality signals such as additional online reviews, superhost status, and a verified ID. Thus, buyers can make a conscious decision to either pay a premium for the listing with better ratings and more additional signals or save money and choose the listing with lower ratings and fewer signals. In the absence of our empirical results, buyers cannot be sure whether increased prices can be the result of ratings and additional quality signals or whether they are just arbitrary price increases by the host.

2 Related Literature

Online ratings in general represent an important feature for online transactions for sellers as a quality signal and for buyers to evaluate the quality of products and services prior to purchase. Online ratings seem to be an exclusive—and thus even more important—information channel in the sharing economy. That is, in contrast to conventional restaurants or hotels, it is difficult to tap alternative sources of information to evaluate the quality of an Airbnb listing. However, several studies report implausibly high ratings across sellers on peer-to-peer markets. Evidence from online labor markets (Horton and Golden 2015) suggests that in bilateral rating systems, the cost of leaving a bad review exceeds the cost of leaving a good review and therefore generates an upward bias on ratings. A field experiment (Fradkin et al. 2015) finds that omitted feedback on Airbnb is on average more negative, even though it is not as large in magnitude as expected. Moreover, Zervas et al. (2015) find evidence for staggeringly high Overall online ratings on Airbnb. Comparing online ratings from TripAdvisor, a conventional non-peer-to-peer reviewing platform, suggests that the same accommodation is rated much higher on Airbnb than on TripAdvisor.

Concerning the relationship between online ratings and prices, a previous study (Li and Hitt 2010) has found that there is substantial interaction between online ratings and prices, which has to be considered when strategically setting optimal prices. In other words, online ratings can enable hosts to increase prices, but prices, in turn, can decrease online ratings. If prices are below a certain price that is considered reasonable by the buyer, prices can also increase subsequent ratings. The authors theoretically analyze profit-maximizing prices and validate their model on a data set for digital cameras. First, concerning the effect of online ratings on prices on Airbnb, several studies find a positive effect of the former on the latter (Gutt and Herrmann 2015, Proserpio et al. 2016, and Teubner et al. 2016). Using a panel data set, Proserpio et al. (2016) find a positive effect of rating disclosure (Airbnb only discloses a host’s rating once the host reaches three individual ratings) on the price, whereas they find

3 In a recent paper, Filippas and Gramstad (2016) theoretically analyze the relationship between price setting on peer-to-peer platforms and awareness attraction, neglecting online ratings and weighting parameters to account for inflated ratings.
an insignificant relationship between prices and the cumulative number of online ratings. On a cross-sectional data set of Airbnb listings in Germany, Teubner et al. (2016) find that average online rating, superhost badges, and verified ID are significantly positively correlated with listing prices, whereas number of reviews are significantly negatively correlated with listing prices. Finally, Gutt and Herrmann (2015) show that rating disclosure on Airbnb causally leads to a modest subsequent price increase. Second, with regard to the effect of prices on ratings, Gutt and Kundisch (2016), using a data set on Airbnb from New York City, find that price increases are associated with a significant decrease in online ratings.

We contribute to both of these literature streams by proposing an analytical model that yields optimal prices conditional on online ratings that account for potentially inflated ratings. Moreover, we validate parts of the predictions of our analytical model and establish a causal relationship between listing-specific quality signals and prices.

3 Analytical Model

We will refer to guests and hosts as buyers and sellers, respectively. First, we describe our model, and second, we present results for the monopoly case before deriving model predictions. Our model is based on the one proposed by Li and Hitt (2010). We begin by analyzing a two-period market. In the first period, buyers known as first movers rent a property or object based on their expectations. In the second period, other buyers are able to observe the aggregated ratings for the multiple dimensions and incorporate the new information into their decision-making process. We summarize the notation of our variables in Table 1.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q_p$</td>
<td>Perceived quality, $q_p \in [0,1]$</td>
</tr>
<tr>
<td>$x_i$</td>
<td>Buyer taste, $x_i \in [0,1]$</td>
</tr>
<tr>
<td>$t$</td>
<td>Mismatch costs, $t \in (1, \infty)$</td>
</tr>
<tr>
<td>$R$</td>
<td>Overall rating, $R \in [0,1]$</td>
</tr>
<tr>
<td>$d(q_p)$</td>
<td>Perceived reasonable price, $\frac{q_p}{2}$</td>
</tr>
<tr>
<td>$r$</td>
<td>Rating system reliability, $r \in [0,1]$</td>
</tr>
<tr>
<td>$S$</td>
<td>Additional quality signals, $S \in [0,1]$</td>
</tr>
</tbody>
</table>

Table 1. Notation

A buyer’s utility is modelled by $U(x_i, q_p, p) = q_p - p - tx_i$ where $p$ is the object’s price.

Assumption 1 (Buyer and Object Characteristics): Buyers are heterogeneous in taste $x_i$. An object is characterized by a perceived quality $q_p$ and mismatch costs $t$.

Parameter $q_p$ describes the quality as perceived by the buyer. It is defined in the interval $[0,1]$ and is the same for all buyers. $q_p$ is learned after consuming the product, but it may differ from the unobservable actual quality due to biases arising from social interaction or bilateral rating systems, for example (Fradkin et al. 2015, Zervas et al. 2015). The underlying intuition is that in sharing markets that involve a high degree of personal interaction, buyers perceive the quality of an object differently than in a hotel. In a hotel setting, buyers can be sensitive to the perception of quality (such as the cleanliness of the bathroom, the noise from outside, and the available amenities). In contrast to that, the perception of the actual underlying quality in the sharing economy might intermingle with aspects related to personal motives. If buyers feel sympathy for the seller, they might perceive quality features of the object (such

Li and Hitt (2010) showed for a related model that their findings derived from the monopoly case remain qualitatively unchanged for a duopoly setup.
as a dirty bathroom sink) differently and not report them when giving an online rating. This represents one possible explanation of why \( q_p \) might differ from the unobservable actual quality and why ratings in the sharing economy are inflated.

The parameter \( x_i \in [0,1] \) is used to incorporate buyer taste. A low \( x_i \) indicates that the rented object matches the buyer’s taste well. For example, the taste of parents might be matched well with a property that offers a parking space, room to play for the kids, and a safe neighborhood, whereas the taste of young party-seeking students might be matched well with a small downtown room in a lively part of the city. The parameter \( t \in (1, \infty) \) represents the mismatch costs of the object. High mismatch costs represent an object, a niche product, that some people really like and others strongly dislike, and mismatch costs close to 1 represent a mainstream product. A newly renovated spacious apartment with good connection to local transport is a mainstream object that all buyers like. A niche product that some buyers love and some buyers strongly dislike can be, for instance, a cabin in the woods without Internet connection and water supply but with a fireplace and situated beautifully in a scenic landscape. Also, buyers know their taste \( x_i \) in advance. Because \( q_p \leq 1 \) and \( t > 1 \), a monopoly cannot cover the whole market.

The first movers begin by making their decisions regarding the purchase. These are based on expected quality \( q_e \) and the price in the first-period \( p_1 \). As in previous studies (Li and Hitt 2010), \( q_e \) is exogenous and common across all buyers. We normalize the value of the best alternative to this product to zero. All first movers with a positive utility \( U(x_i, q_e, p_1) \) will buy the object. From the position of the indifferent buyer, we derive the first-period demand \( \frac{d_e - p_1}{t} \).

**Assumption 2 (Rating Behavior): Every first mover posts her truthful overall rating of \( R \).**

This is in line with previous theoretical work on rating behavior (Sun 2012). Although \( R \) is reported truthfully, it may still be biased because \( q_p \) can deviate from the unobservable actual quality. This is in line with the notion that some buyers might not report negative quality features of an object due to personal interaction with the seller.

**Assumption 3 (Price Effects): Overall ratings \( R \) are influenced by a price effect of \( b \left( p_1 - d(q_p) \right) \).**

Parameter \( b \in (0,1) \) reflects the effect of price changes on the overall rating \( R \), and \( d(q_p) \) is the price seen as “reasonable” by all the buyers. If the price is higher than what is thought of as reasonable, ratings will decrease. With a price below the reasonable one, ratings will increase. For the monopoly case, we set \( d(q_p) = \frac{q_p}{2} \), which equals the standard monopoly price for products with perceived quality \( q_p \). We can later test Assumption 2 on our data set. The generation of \( R \) is then described by Equation (1).

\[
R = \max\{0, \min\{1, q_p - b(p_1 - d(q_p))\}\}
\] (1)

The Rating \( R \) is normalized to the interval of \([0,1]\). Again, note that if \( q_p \) is larger than actual quality, ratings \( R \) are inflated. Consequently, perceived quality and the resulting ratings observable in the second period may be more or less reliable. Therefore, second-period buyers try to assess the product’s quality by looking for additional quality signals (such as number of ratings, whether the host verified himself with an ID, other certifications or badges, and so on). This effect is captured by \( S \in [0,1] \). Buyers analyze ratings and additional quality signals to form their quality expectations:

\[
r \cdot R + (1 - r) \cdot S
\] (2)

Parameter \( r \in [0,1] \) normalizes the expectations to the interval \([0,1]\). Intuitively, \( r \) is the second-period buyers’ assessment of the rating system’s reliability. In case of inflated ratings, perceived quality is a weak signal for actual quality. Thus, ratings should be considered less in quality expectations of second-period buyers, which corresponds to \( r \) being close to 0. Generally, buyers could take both online ratings and additional quality signals equally into account (\( r \) close to 0.5).

**Assumption 4 (First-Period Price-Independent Quality Signals): Additional quality signals \( S \) do not depend on the first-period price \( p_1 \).*
This is not a trivial assumption. For example, sellers could set $p_1$ to a low value to achieve more reviews and increase $S$. However, the trade-off between a higher first-period price and additional reviews may be hard to assess for sellers. Also, there are a lot of other price-independent aspects contributing to the additional quality signal (such as badges and a verified ID). Furthermore, we will show that sellers should reduce first-period prices if they expect a high additional quality signal in the second period, even though we make this simplifying assumption of price independence. In the following, we will present optimal prices $p_1$ and $p_2$ given the buyers’ demand and reviewing behavior. Let $n$ $(n > 0)$ be the ratio of second- to first-period buyers. The monopolist selects $p_1$ and $p_2$ to maximize total profit:

$$
\pi(p_1, p_2) = \frac{p_1(q_e - p_1)}{t} + n \left( \frac{p_2 \cdot r \cdot R + (1 - r) \cdot S - p_2}{t} \right)
$$

where $p_1 < q_e$ and $p_2 < r \cdot R + (1 - r) \cdot S$

Optimal prices for this profit function are as follows:

$$
p_1 = \begin{cases} 
\frac{q_e}{2} & \text{if } 0 < q_e < \overline{Q}_1 \text{ or } \frac{b q_e + 2}{b + 2} \leq q_p < 1 \\
\max \left\{ 0, \frac{(2 + b)q_p - 2}{2b} \right\} & \text{if } \overline{Q}_1 < q_p < \max \left\{ \overline{Q}_1, \min \left( \frac{2 b (r - 1) S + 4 q_e}{(b^2 + 2 b) n r^2}, b \frac{q_p}{b + 2} \right) \right\}
\end{cases}
$$

Optimal prices for this profit function are as follows:

$$
p_2 = \begin{cases} 
\frac{S(1 - r) + r (b + 2) q_p - 2 b p_1^*}{2} & \text{if } \overline{Q}_1 < q_p < \max \left\{ \overline{Q}_1, \frac{2}{2 + b} \right\} \\
\frac{S(1 - r) + r (b + 2) q_p - 4 b p_1^*}{2} & \text{if } q_p < \overline{Q}_1
\end{cases}
$$

where

$$
\overline{Q}_1 = \begin{cases} 
\sqrt{2 \left( (n^2 r^2 - 2 n^2 r^2 + n^2) S^2 + n q_e^2 + 2 n S (r - 1) \right)} & \text{if } n > \frac{4}{b^2 r^2} \\
\frac{(1 - r) \sqrt{- b^2 n r^2 S + b q_e r - 2 S (1 - r)}}{(b + 2) r} & \text{if } n < \frac{4}{b^2 r^2}
\end{cases}
$$

Derivations of optimal prices and explanations of $\overline{Q}_1$ and $\overline{Q}_2$ are provided in the appendix.

4 Model Predictions

To illustrate the model predictions, we present graphs for different values of $q_p$, $r$, and $S$ with $b = 0.3$, $q_e = 0.5$, $n = 3$ and $t = 1.5$ in Figure 1. The results remain similar for different settings.

**Prediction 1:** Providers with neither high nor low perceived quality $q_p$ have an incentive to reduce first-period price $p_1^*$ ($p_1^* < \frac{q_e}{2}$ for $\overline{Q}_1 < q_p < \frac{b q_e + 2}{b + 2}$).

**Prediction 2:** The incentive to reduce first-period prices depends on the rating system’s reliability $r$ and the additional quality signal $S$. For $0 < r < 1$ and $n < \frac{4}{b^2 r^2}$ a high additional quality signal leads to further first-period price reduction ($\frac{\partial p_1^*}{\partial S} < 0$ for $0 < r < 1$, $n < \frac{4}{b^2 r^2}$ and $\overline{Q}_1 < q_p < \max \left\{ \overline{Q}_1, \min \left( \frac{2 b (r - 1) S + 4 q_e}{(b^2 + 2 b) n r^2}, b \frac{q_p}{b + 2} \right) \right\}$). This effect is strong for values of $r$ close to 0.5.
Depending on the rating system’s reliability \((r)\), sellers in the medium-quality segment have an incentive to price below the monopoly price of \(p_{1,2} = 0.25\) to improve their ratings, as depicted in Figure 1 a) and b), and thus increase second-period profit. Sellers in the high-quality segment do not have an incentive to reduce the first-period price because they achieve a maximum rating even without a price reduction. Similarly, sellers in the low-quality segment do not have an incentive to reduce first-period prices because it is more profitable to set the monopoly price before ratings reveal the low perceived quality. Intuitively, this effect is strong if people fully rely on ratings and weak if they mostly rely on additional quality signals. Interestingly, for a market in which buyers consider both ratings and additional quality signals, first-period prices decrease with an increasing additional quality signal. This effect even applies if additional quality signals are independent of first-period prices (for example, sellers plan to verify their ID in the second period, or they are awaiting an award or a badge). The reason for this prediction follows from the importance of both ratings and additional quality signals. A higher additional quality signal will increase the second-period price. The seller anticipates this price increase and reduces the first-period price to boost ratings and thus the sold quantity. The increase in sold quantity is used to further exploit the anticipated increase in price.

\[
\frac{\partial p_2^*}{\partial q_p} > 0 \text{ for } 0 < q_p < \max \left( \frac{1}{2}, \frac{1}{2 + b} \right). \text{ The magnitude of this effect is increasing in } r.
\]

Prediction 4: Second period price \(p_2^*\) increases with an increasing additional quality signal \(S\)
\[
\frac{\partial p_2^*}{\partial S} > 0.
\]
If second-period buyers rely less on ratings to form their expectations (low \( r \)), the perceived quality of first-period buyers is only taken into account to a lower degree; therefore, second-period prices increase only a little with increasing perceived quality. Because second-period buyers use additional quality signals to form their quality expectations, all sellers are able to use these signals to demand a higher second-period price (Figure 1, c).

**Prediction 5:** If buyers consider both additional quality signals and ratings (\( 0 < r < 1 \)), total profit increases as quality signal \( S \) increases. With higher perceived quality \( q_p \), these gains in total profit increase.

\[
\frac{\partial}{\partial q_p} \left( \frac{\partial n(p_1^*, p_2^*)}{\partial S} \right) > 0 \text{ for } \bar{Q}_1 < q_p < \max \left\{ \bar{Q}_2^*, \frac{2}{2+b} \right\}.
\]

Sellers offering a higher perceived quality are able to realize larger total profit gains by investing in additional quality signals than their competitors offering a lower perceived quality—that is, counterintuitively, a higher perceived quality is an incentive to invest even more in additional quality signals (see Figure 1, d). All competitors would raise second-period prices with a higher additional quality signal. But offering a higher perceived quality improves the received ratings and thereby the sold quantity. This increased quantity enables a better exploitation of higher second-period prices.

### 4.1 Hypotheses

To test whether there exists a positive effect of additional quality signals \( S \) on second-period prices, we analyze data from Airbnb. We deem this platform to be a suitable choice because ratings seem inflated; therefore, we believe that users will use additional quality signals to assess the quality of a listing. In our empirical analysis, we focus on Prediction 4, for which we can operationalize the relevant variables based on our data. We delineate the following hypotheses, which we later test on our rich data set.

First, the sheer number of reviews of a listing can be considered an additional quality signal. It reflects that a listing is regularly frequented by guests, and each review text can contain incremental information that helps unveil the underlying quality of the listing. Additionally, a large number of reviews indicates that a large number of people chose this listing over other ones. Therefore, our first hypothesis reads as follows:

**Hypothesis H1:** Sellers on a peer-to-peer market demand a higher price after having received additional reviews for a listing.

Second, on Airbnb, both the number of reviews and the badges assigned to the host can be indicators of quality. A host is assigned the superhost badge if she has a high response rate, rarely cancels reservations, has at least ten reservations per year, and receives at least 80% 5-star reviews. Consequently, we formulate our second hypothesis:

**Hypothesis H2:** Sellers on a peer-to-peer market demand a higher price after being marked with a superhost badge.

Third, although superhost is a badge that is relatively rarely assigned, a lot of hosts are assigned a verified ID badge. To receive the latter, hosts have to provide identification (such as taking a picture of oneself, providing a photo of a government-issued ID, and connecting via another online profile). Thus, we formulate our third hypothesis:

**Hypothesis H3:** Sellers on a peer-to-peer market demand a higher price after being marked with a verified ID badge.

We test the three hypotheses using our empirical model in equation (8). In particular, Hypothesis H1 is tested based on the coefficient \( \beta_1 (5\_MORE\_REV_i \cdot POST\_TREAT1) \). Hypothesis H2 is tested based on the coefficient \( \beta_2 (SUPERHOST \cdot POST\_TREAT2) \), and Hypothesis H3 is tested based on the coefficient \( \beta_3 (VERIFIED\_ID_i \cdot POST\_TREAT3) \).
5  Empirical Analysis

We use a web crawler to collect data from Airbnb from July 12, 2016 until October 11, 2016 on a two-week basis. This panel data consists of a total of 143,405 observations for 41,870 distinct listings that were managed by 27,526 hosts. The listings are located in eight U.S. cities, namely Boston, Chicago, Indianapolis, Nashville, Phoenix, Pittsburgh, Portland, and San Francisco. The information includes price per night, cleaning fee, price for extra people, number of people, number of beds, room type (entire home, private room, shared room), aggregated ratings for seven dimensions (overall, accuracy, communication, cleanliness, location, check-in, value/price performance), number of reviews, existence of a superhost badge, and existence of a verified ID badge. Table 2 provides corresponding descriptive statistics. The range of the mean values of all ratings (4.76–4.91) suggests that ratings are inflated. In summary, a “typical” rental on Airbnb, on average, costs $178.05 per night, accommodates 3.25 guests, has 1.72 beds, has 21.60 reviews, and has rating scores between 4.74 (Value rating) and 4.91 (Communication and Check-in rating). Approximately 57% of all rentals are entire homes and 40% are private rooms, so a typical rental is either an entire home or a private room.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price per night (in US $)</td>
<td>178.05</td>
<td>299.59</td>
<td>9.95</td>
<td>10396.47</td>
</tr>
<tr>
<td>Absolute price difference ( (t_t - t_{t-1}) ) in %</td>
<td>2.35</td>
<td>26.70</td>
<td>0</td>
<td>78.64</td>
</tr>
<tr>
<td>Cleaning fee (in US $)</td>
<td>43.63</td>
<td>53.75</td>
<td>0</td>
<td>1039.65</td>
</tr>
<tr>
<td>Extra people price (in US $)</td>
<td>16.22</td>
<td>49.05</td>
<td>0</td>
<td>1874.07</td>
</tr>
<tr>
<td>Number of people</td>
<td>3.25</td>
<td>2.13</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Number of beds</td>
<td>1.72</td>
<td>1.21</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Room type: Entire home</td>
<td>0.57</td>
<td>0.50</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Room type: Shared room</td>
<td>0.03</td>
<td>0.18</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Room type: Private room</td>
<td>0.40</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Number of reviews</td>
<td>21.60</td>
<td>39.18</td>
<td>0</td>
<td>868</td>
</tr>
<tr>
<td>Superhost</td>
<td>0.18</td>
<td>0.39</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Verified ID</td>
<td>0.73</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Overall rating</td>
<td>4.77</td>
<td>0.34</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Accuracy rating</td>
<td>4.84</td>
<td>0.30</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Communication rating</td>
<td>4.91</td>
<td>0.23</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Cleanliness rating</td>
<td>4.76</td>
<td>0.38</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Check-in rating</td>
<td>4.91</td>
<td>0.23</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Location rating</td>
<td>4.78</td>
<td>0.34</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Value rating</td>
<td>4.74</td>
<td>0.33</td>
<td>1</td>
<td>5</td>
</tr>
</tbody>
</table>

Table 2. Descriptive statistics for different variables. \( N=143,405 \). Note that rating variables exist only for listings with at least three reviews.

5.1  Empirical Model and Results

First of all, to test our model assumption regarding the effect of prices on the overall rating as depicted in equation (1), we estimate a fixed effects model similarly to Li and Hitt (2010), in which we regress the overall rating of the current period on the natural logarithm of the price of the previous period. We control for the number of reviews, the other rating dimensions, the number of beds and people, and the room type, and we cluster standard errors on the host level to account for the potential correlation between multiple listings managed by one host. A change in room type from entire home to private room...
might affect the price strongly and makes controlling for it necessary. The results depicted in Table 3 suggest that an increase in the previous period price leads to a 0.023 stars decrease in overall rating (p-value: 0.044). With a price increase of 10%, an overall rating of 4.9 would be decreased to 4.67 and in total result in being changed from a rounded 5-star rating to a rounded 4.5-star rating. This result supports Assumption 3 of our model, which states that price increases are associated with a decrease in overall ratings.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Overall Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>$LOG_{PRICE}_{t-1}$</td>
<td>-0.02263***</td>
</tr>
<tr>
<td></td>
<td>(0.01123)</td>
</tr>
<tr>
<td>Listing fixed effects</td>
<td>✓</td>
</tr>
<tr>
<td>Other controls</td>
<td>✓</td>
</tr>
<tr>
<td>Constant</td>
<td>1.98593***</td>
</tr>
<tr>
<td></td>
<td>(0.75745)</td>
</tr>
<tr>
<td>Observations</td>
<td>143,405</td>
</tr>
<tr>
<td>Within-R²</td>
<td>0.166</td>
</tr>
</tbody>
</table>

Table 3. Coefficients for previous-period natural logarithm of price. Regression for a listing’s overall rating. Robust standard errors are in parentheses.

*** $p < 0.01$; ** $p < 0.05$.

For Airbnb, it is likely that the unobserved time-invariant location (such as proximity to touristic points of interest) has an effect on overall rating as well as pricing. There also may be other unobserved time-invariant effects. A fixed effects model will eliminate endogeneity arising from these effects. Using the previous period for the variable of interest also solves any possible reverse causality problems. However, it also imposes an ongoing adjustment process. In our case, it imposes that reviewers rent the property based on the previous period price and use this information to write a corresponding review in the following period. Although this approach is appropriate to test our model assumption, it is not suitable to test our hypotheses because there is not necessarily a time difference between receiving a review or a badge and adjusting the price. Instead, we use a differences-in-differences ($DiD$) approach but also incorporate a fixed effects approach to account for time invariant unobservable heterogeneity. The coefficients of these interaction terms measure the average treatment effect on the treated ($ATT$) as long as the common trends assumption holds. We define three different treatments depending on whether (i) a listing has received five additional review(s), (ii) a listing’s host has received the verified ID badge, or (iii) a listing’s host has received the superhost badge.

Considering all treatments we have defined, we formulate the following model equation:

\[
LOG_{PRICE_{it}} = \alpha + \beta_15\_MORE\_REV_{it} \cdot POST\_TREAT1_{it} + \beta_2SUPERHOST \cdot POST\_TREAT2_{it} + \beta_3VERIFIED\_ID_{it} \cdot POST\_TREAT3_{it} + \beta_4TIME_{t} + \beta_5\gamma_{it} + \beta_6\delta_{it} + \varepsilon_{it}
\]

Our outcome variable is the natural logarithm of the current period price. We incorporate interaction terms of our treatment variables with a corresponding post-treatment indicator. Treatment variables are set to 1 for every period if a change of status occurs in any period. (This might be superhost or verified ID badge being obtained or five or more reviews being received.) $TIME$ is a vector of time step dummies. Furthermore, we control for a vector of time-variant variables $\gamma$ consisting of number of reviews, number of beds, number of people, cleaning fee, price for extra people, and room type. $\delta$ is a vector of listing fixed effects, and $\varepsilon_{it}$ describes the remaining unobserved time-variant error term.
Table 4. Coefficients for different interaction terms from a DiD-model with fixed effects for the natural logarithm of price. Robust standard errors are in parentheses.

<table>
<thead>
<tr>
<th>Variable</th>
<th>LOG_PRICE</th>
</tr>
</thead>
<tbody>
<tr>
<td>5_MORE_REV * POST_TREAT1</td>
<td>0.00489***</td>
</tr>
<tr>
<td></td>
<td>(0.00159)</td>
</tr>
<tr>
<td>VERIFIED_ID * POST_TREAT2</td>
<td>0.01593**</td>
</tr>
<tr>
<td></td>
<td>(0.00667)</td>
</tr>
<tr>
<td>SUPERHOST * POST_TREAT3</td>
<td>0.00672**</td>
</tr>
<tr>
<td></td>
<td>(0.00285)</td>
</tr>
<tr>
<td>Time dummies</td>
<td>✓</td>
</tr>
<tr>
<td>Listing fixed effects</td>
<td>✓</td>
</tr>
<tr>
<td>Other controls</td>
<td>✓</td>
</tr>
<tr>
<td>Constant</td>
<td>4.5896***</td>
</tr>
<tr>
<td></td>
<td>(0.08086)</td>
</tr>
<tr>
<td>Observations</td>
<td>143,405</td>
</tr>
<tr>
<td>Within-R²</td>
<td>0.0328</td>
</tr>
</tbody>
</table>

Our results suggest that, first, after having received five additional reviews, hosts increase prices by 0.49% on average, as depicted in Table 4. This increase is positive and statistically significantly different from zero; thus, we find support for Hypothesis H1. Results are similar if we use one additional review instead of five as a treatment. Second, after having received a verified ID badge, hosts increase their prices by 1.59% on average. This increase is positive and statistically significantly different from zero; thus, we also find support for our Hypothesis H2. Third, after having received a superhost badge, hosts increase prices by 0.67%. This increase is positive and statistically significantly different from zero; therefore, we also find support for our Hypothesis H3. These effects seem small, but 90% of absolute price changes are within a range of 0 to 1.92%. Therefore, our findings help explain a substantial share of the observed variation in prices. To test whether the common trends assumption is supported, we conducted a placebo regression by moving starting points of the treatments back and forth in time (Bertrand et al. 2004). No statistical significance was found in these setups. Based on this, we find no violation of the common trends assumption.

6 Conclusion

Price setting is, by nature, challenging. For hosts in the sharing economy, this task is even more difficult, and prior research has not provided an adequate solution. This is because hosts need to account for (i) interactions between prices and online ratings and (ii) a potentially inflated rating system, when determining optimal prices. Moreover, hosts can provide additional quality signals that consumers can use to infer the underlying quality of a product. Our paper attempts to close this research gap and solve this pricing problem by presenting a theoretical model and empirical validations thereof.

Consequently, this study, to the best of our knowledge, is the first to propose a theoretical model to the literature that derives optimal prices incorporating interactions between prices and online ratings, inflated online ratings, and additional quality signals. First, theoretically, we find that hosts in the medium-quality segment have an increasing incentive to lower prices to improve their online ratings which, in turn, can increase prices and profits in the second period. Additionally, this effect is strongest for the highest qualities in the medium-perceived quality segment. Second, we find that this effect depends on the reliability of the online ratings. The incentive to reduce prices to improve ratings is
lowered when online ratings are inflated. Third, we find that after receiving ratings, prices and profits increase with the availability of additional quality signals such as additional reviews, badges, and ID verification of the host. This finding is empirically validated using a comprehensive panel data set from Airbnb and applying a robust econometric DiD model.

Our work comes with important practical implications and implications for future research. First, our findings are valuable to homeowners in the sharing economy because our results can guide price setting for their property as they observe their perceived quality and additional quality signals. For example, homeowners who are new to Airbnb can identify listings that are similar to their homes but already have a number of reviews and additional quality signals. Homeowners can then calculate their initial listing price by slightly undercutting the price of the similar listings, anticipating reviews and additional quality signals they can monetize on in the future. Second, we provide the theoretical basis for future research that attempts to strike a balance between the online rating score and additional quality signals. This is especially applicable for, but explicitly not limited to, the sharing economy where ratings are inflated. For example, consider a consumer deciding between a product with an average rating of 5 from 10 reviews and a product with an average rating of 4.5 from 60 reviews. With high probability, the consumer will choose the latter. Therefore, we also contribute to the discussion between volume and valence of online ratings (Trenz and Berger 2013).

As any research, this study also comes with limitations. We do not provide an answer on how to calculate or measure the combined value of quality signals of a product. Also, we assume that there is no relationship between first-period prices and second-period additional quality signal. One could incorporate the number of reviews generated by first-period price into the additional quality signal to relax this assumption. Moreover, our model is only tested for a peer-to-peer market, for which we deem it most applicable. Future research could extend these limitations and include a welfare analysis. Finally, our data set only spans a time period from June 2016 to October 2016. Future research could extend this time period to fully account for seasonal demand changes or special events that might drive demand.

Appendix

We must determine $p_1$ and $p_2$ to maximize total profit as defined in Equation (3). We use backward induction and determine the optimal second-period price $p_2^*$ with $p_2 < r \cdot R + (1 - r) \cdot S$ for second-period profit:

$$\pi_2(p_2) = n \left( p_2 \cdot \frac{r \cdot (\max \{0, \min \{1, q_p - b(p_1 - d(q_p))\}\} + (1 - r) \cdot S - p_2)}{t} \right)$$

(9)

Depending on $p_1$, one can make a case distinction to represent Equation 9 with three different terms:

$$\pi_2(p_2) = \begin{cases} 
np_2 \cdot \frac{r + (1 - r)S - p_2}{t} & \text{if } 0 < p_1 < \frac{(2 + b)q_p - 2}{2b} \\
np_2 \cdot \frac{r \left( q_p - b \left( p_1 - \frac{q_p}{2} \right) \right) + (1 - r)S - p_2}{t} & \text{if } \frac{(2 + b)q_p - 2}{2b} < p_1 < \frac{(2 + b)q_p}{2b} \\
np_2 \cdot \frac{(1 - r)S - p_2}{t} & \text{if } \frac{(2 + b)q_p}{2b} < p_1 < q_e 
\end{cases}$$

(10)

Taking the derivative of $\pi_2(p_2)$ with respect to $p_2$ yields the optimal price $p_2^*$:

$$\pi_2(p_1) = \begin{cases} 
\frac{S(1 - r)}{2} & \text{if } 0 < p_1 < \frac{(2 + b)q_p - 2}{2b} \\
\frac{S(1 - r)}{2} + \frac{r \left( (b + 2)q_p - 2bp_1 \right)}{4} & \text{if } \frac{(2 + b)q_p - 2}{2b} < p_1 < \frac{(2 + b)q_p}{2b} \\
\frac{S(1 - r)}{2} & \text{if } \frac{(2 + b)q_p}{2b} < p_1 < q_e 
\end{cases}$$

(11)
We insert the value of \( p_2^*(p_1) \) into Equation 10 to receive the optimal second-period profit \( \pi_2^*(p_1) \):

\[
\pi_2^*(p_1) = \begin{cases} 
\frac{n(S(1-r) + r)^2}{4t} & \text{if } 0 < p_1 < \frac{(2+b)q_p - 2}{2b} \\
\frac{n \left( b(r(q_p - 2p_1) + 2 (q_p + S(1-r))) \right)^2}{16t} & \text{if } \frac{(2+b)q_p - 2}{2b} < p_1 < \frac{(2+b)q_p}{2b} \\
\frac{nS^2(r-1)^2}{4t} & \text{if } \frac{(2+b)q_p}{2b} < p_1 < q_e 
\end{cases}
\] (12)

Total profit \( p_2^*(q_e-p_1) + \pi^*_2(p_1) \) can be optimized by derivation with respect to \( p_1 \). This yields the solution of \( p_1^* \) of Equation 4. The first case describes the optimal price for very low and very high quality. The two following cases describe a corner and an inner solution. The different thresholds (including \( \tilde{Q}_1 \) and \( \tilde{Q}_2 \)) are computed by (i) solving the inequality of one of the cases from Equation 12 for \( q_p \), (ii) solving the inequality between two profit functions with different candidate solutions (also inner and corner solution) for \( q_p \), or (iii) solving the equality between two already calculated thresholds for \( n \). The latter makes sure that, if two thresholds overlap, another threshold is chosen (reason for case distinction in \( \tilde{Q}_1 \)). Finally, the cases formed with these thresholds can be used to determine which value of \( p_2^* \) is used for which value of \( q_p \). This is necessary to conclude Equation 5 from Equation 11.

The key idea of all proofs is the usage of \( b > 0, n > 0, 1 > r > 0, t > 0 \):

**Proof of Prediction 1.** If \( p_1^* = \frac{(2+b)q_p - 2}{2b} \), it is maximal for \( q_p = \frac{bq_p + 2}{b+2} \). Then, \( p_e - p_1^* = 0 \).

Thus, \( q_e^* - p_1^* > 0 \) for smaller \( q_p \). If \( p_1^* = \frac{bnr((b+2)q_p + S(1-r)) - 4q_e}{(b+2)r} \), it is maximal for \( q_p = \frac{(1-r)^2}{4 - b - 2 Mr^2 + 2b^2r^2} \). Then, \( \frac{q_e^* - p_1^*}{2} = \frac{bnr(r-1)^2 - b + 2Mr^2 - 8}{2b^2r^2 - 8} < 0 \) since \( n < \frac{4}{b r^2} \) in this case.

**Proof of Prediction 2.**

\[
\frac{d}{dS} \left[ \frac{bnr((b+2)q_p + S(1-r))^2}{(b+2)r} - 4q_e \right] = \frac{2bnr(r-1)^2}{2b^2r^2 - 8} < 0, \text{ since } n < \frac{4}{b^2r^2}.
\]

**Proof of Prediction 3.**

\[
\frac{d}{dp_q} \left[ \frac{bnr((b+2)q_p + S(1-r))^2}{(b+2)r} - 4q_e \right] = \frac{(b+2)r}{4} > 0.
\]

**Proof of Prediction 4.** Denote the three solutions of \( p_2^* \) as \( O_1, O_2, O_3 \) respectively. Then, \( \frac{dO_1}{dS} = \frac{1-r}{2} > 0 \) and \( \frac{dO_2}{dS} = \frac{1-r}{2} - \frac{2b r^2}{4} > 0 \) since \( \frac{p_1^*}{dS} \leq 0 \) (Prediction 2; for other cases of \( p_1^* ; \frac{dO_2}{dS} = 0 \)).

**Proof of Prediction 5.** Since \( \frac{\tilde{Q}_1}{2} < \frac{\tilde{Q}_2}{2} \), \( p_2^* \) is either 0 or \( \frac{bnr((b+2)q_p + S(1-r)) - 4q_e}{2b^2r^2 - 8} \).

Therefore, optimal second period profit \( \pi^*_2(p_1) \) is equal to

\[
\frac{n \left( b(r(q_p - 2p_1) + 2 (q_p + S(1-r))) \right)^2}{16t}, \quad \text{if } p_1^* = \frac{bnr((b+2)q_p + S(1-r)) - 4q_e}{2b^2r^2 - 8}.
\]

\[
\frac{d}{dp_q} \left[ \frac{n \left( b(r(q_p - 2p_1) + 2 (q_p + S(1-r))) \right)^2}{16t} \right] = \frac{bnr((b+2)q_p + S(1-r)) - 4q_e}{2b^2r^2 - 8} > 0, \text{ since } n < \frac{4}{b^2r^2} \text{ in this case. If } p_1^* = 0, \frac{d}{dp_q} \left[ \frac{n \left( b(r(q_p - 2p_1) + 2 (q_p + S(1-r))) \right)^2}{16t} \right] = \frac{-bnr(b+2)(r-1)}{4t} > 0.
\]

**References**


