A Homeowner's Guide to Airbnb: Theory and Empirical Evidence for Optimal Pricing Conditional on Online Ratings[1]

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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. The possibility of monetizing on second-period ratings depends on the buyers' assessment of the rating system's reliability. 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 are associated with 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.

Keywords: Sharing Economy, Online Ratings, Optimal Price Setting, DiD-Regression.
JEL Classification: M15, M31, O32, D12

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1 Introduction

Peer-to-peer markets such as Airbnb, Uber, and Homeaway have witnessed unprecedented economic growth over the past few years. On Airbnb homeowners can rent out their unused space to potential guests. Currently, 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.

Although theoretical and empirical analyses of price setting strategies have drawn significant interest from the information systems literature (e.g., Ajorlou et al. 2016, Cabral and Hortacsu 2010), 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 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. Taking into account the quality features of a listing (e.g., the location, 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 might not be clearly distinguishable between financial and social motivation; given the number of hosts with multiple listings and results in related studies (e.g., Zhang et al. 2018, Gutt and Herrmann 2015), it seems evident that a substantial number of hosts are financially motivated.

Websites like Airbnb operate an online rating system to help erode the large information asymmetry between hosts and guests to establish trust between these two parties (Fradkin et al. 2015). Potential guests can rely on information such as (i) online rating scores or (ii) additional quality signals (e.g.,

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

badges or the number of reviews). With respect to price setting, online ratings possess a dual role (Li and Hitt 2010). High ratings can be a good signal of quality that enables a host to ask for higher prices. 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. However, 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) for a variety of reasons – e.g., an underreporting bias (Dellarocas and Wood 2008). Due to this, 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 a theoretical model 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. 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 of 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 are associated with lower ratings and (ii) validate our model in that we find evidence to support the claim that prices increase with increasing availability of certain additional quality signals.

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 but additional quality signals are available.[3] 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. 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.

2 Related Literature

Online ratings in general represent an important feature of online transactions. Sellers can use them to signal quality and buyers use them 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. Airbnb, for example, provides less codified information in the form of international star rating standards or hotel chain brands that might be used as a substitute for online reviews. 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 one 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. Their comparison with 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 higher prices, in turn, can decrease online ratings. If prices are below a certain level

[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.

that is considered reasonable by the buyer, these prices can also increase subsequent ratings. Li and Hitt (2008) theoretically analyze profit-maximizing prices and validate their model on a data set for digital cameras. Several studies find a positive effect of Airbnb online ratings on prices (Gutt and Herrmann 2015, Proserpio et al. 2018). Using panel data, Proserpio et al. (2018) find a positive effect of rating disclosure (Airbnb displays rating scores once the host reaches three ratings) on the price, whereas they find an insignificant relationship between prices and the cumulative number of online ratings. Finally, Gutt and Herrmann (2015) show that rating disclosure on Airbnb leads to a modest subsequent price increase. With regard to the correlation of prices and 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.

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.[4] Our model is based on the one proposed by Li and Hitt (2010). We begin by analyzing a two-period market. A summary of these stages can be found in Figure 1.

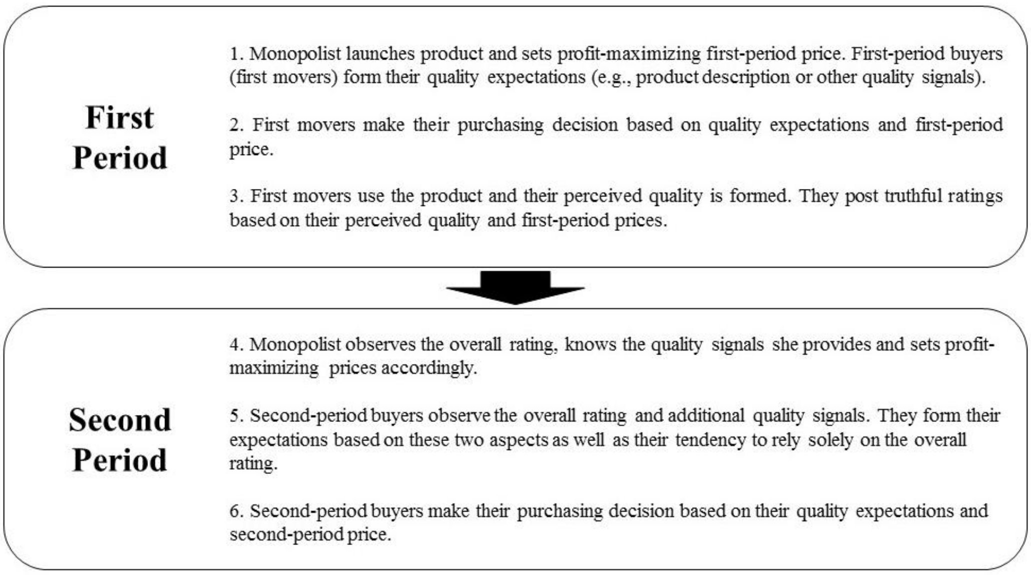


Figure 1. Stages of the Analytical Model

[4] Li and Hitt (2010) showed for a related model that their findings derived from the monopoly case remain qualitatively unchanged for a duopoly setup.

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 1: Notation

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

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 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, whereas 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 others strongly dislike can be, for instance, a cabin in the woods without WiFi access and water supply but with a lovely fireplace and situated beautifully in a scenic landscape. 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 $\frac{q_e - p_1}{t}$.

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).

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

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 (e.g., the number of reviews, certifications, or badges). This effect is captured by $S \in [0,1]$. Buyers analyze ratings and additional quality signals to form their quality expectations:

$$r \cdot R + (1 - r) \cdot S \tag{2}$$

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:

$$\pi(p_1, p_2) = \frac{p_1(q_e - p_1)}{t} + n\left(p_2 \cdot \frac{r \cdot R + (1 - r) \cdot S - p_2}{t}\right) \tag{3}$$
$$\text{where } p_1 < q_e \text{ and } p_2 < r \cdot R + (1 - r) \cdot S$$

Optimal prices for this profit function are as follows (derivations and proofs in appendix):

$$p_1^* = \begin{cases} \frac{q_e}{2} \text{ if } 0 < q_p < \overline{Q}_1 \text{ or } \frac{bq_e+2}{b+2} \leq q_p < 1 \\ \max\left\{0, \frac{(2+b)q_p - 2}{2b}\right\} \text{ if} \max\left\{\overline{Q}_1, \min\left\{\overline{Q}_2, \frac{2bnr(r-1)S + 4q_e}{(b^2+2b)nr^2}\right\}\right\} < q_p < \frac{bq_e+2}{b+2} \\ \frac{bnr\left((b+2)q_p r + S(1-r)\right) - 4q_e}{2b^2nr^2 - 8} \text{ if } \overline{Q}_1 < q_p < \max\left\{\overline{Q}_1, \min\left\{\overline{Q}_2, \frac{2bnr(r-1)S + 4q_e}{(b^2+2b)nr^2}\right\}\right\} \end{cases} \quad (4)$$

$$p_2^* = \begin{cases} \frac{S(1-r)+r}{2} \text{ if } \max\left\{\overline{Q}_2, \frac{2}{2+b}\right\} < q_p < 1 & \text{(high perceived quality segment)} \\ \frac{S(1-r)}{2} + \frac{r\left((b+2)q_p - 2bp_1^*\right)}{4} \text{ if } \overline{Q}_1 < q_p < \max\left\{\overline{Q}_2, \frac{2}{2+b}\right\} & \text{(medium perceived quality segment)} \\ \frac{S(1-r)}{2} \text{ if } 0 < q_p < \overline{Q}_1 & \text{(low perceived quality segment)} \end{cases} \quad (5)$$

where

$$\overline{Q}_1 = \begin{cases} \frac{2\left(\sqrt{(n^2r^2 - 2n^2r^2 + n^2)S^2 + nq_e^2} + 2nS(r-1)\right)}{(b+2)nr} \text{ if } n > \frac{4}{b^2r^2} \\ \frac{(1-r)\sqrt{4 - b^2nr^2}S + bq_e r - 2S(1-r)}{(b+2)r} \text{ if } n < \frac{4}{b^2r^2} \end{cases} \quad (6)$$

$$\overline{Q}_2 = \frac{b^2nr(r-1)S - b^2nr^2 + 2bq_e + 4}{2b+4} \quad (7)$$

3.1 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 2. 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^* $\left(p_1^* < \frac{q_e}{2}\right.$ for $\left.\overline{Q}_1 < q_p < \frac{bq_e+2}{b+2}\right)$.

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 $n < \frac{4}{b^2r^2}$ a high additional quality signal leads to further first-period price reduction $\left(\frac{\partial p_1^*}{\partial S} < 0\right.$ for $0 < r < 1, n < \frac{4}{b^2r^2}$ and $\overline{Q}_1 < q_p <$ $\left.\max\left\{\overline{Q}_1, \min\left\{\overline{Q}_2, \frac{2bnr(r-1)S+4q_e}{(b^2+2b)nr^2}\right\}\right\}\right)$. 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 2 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.

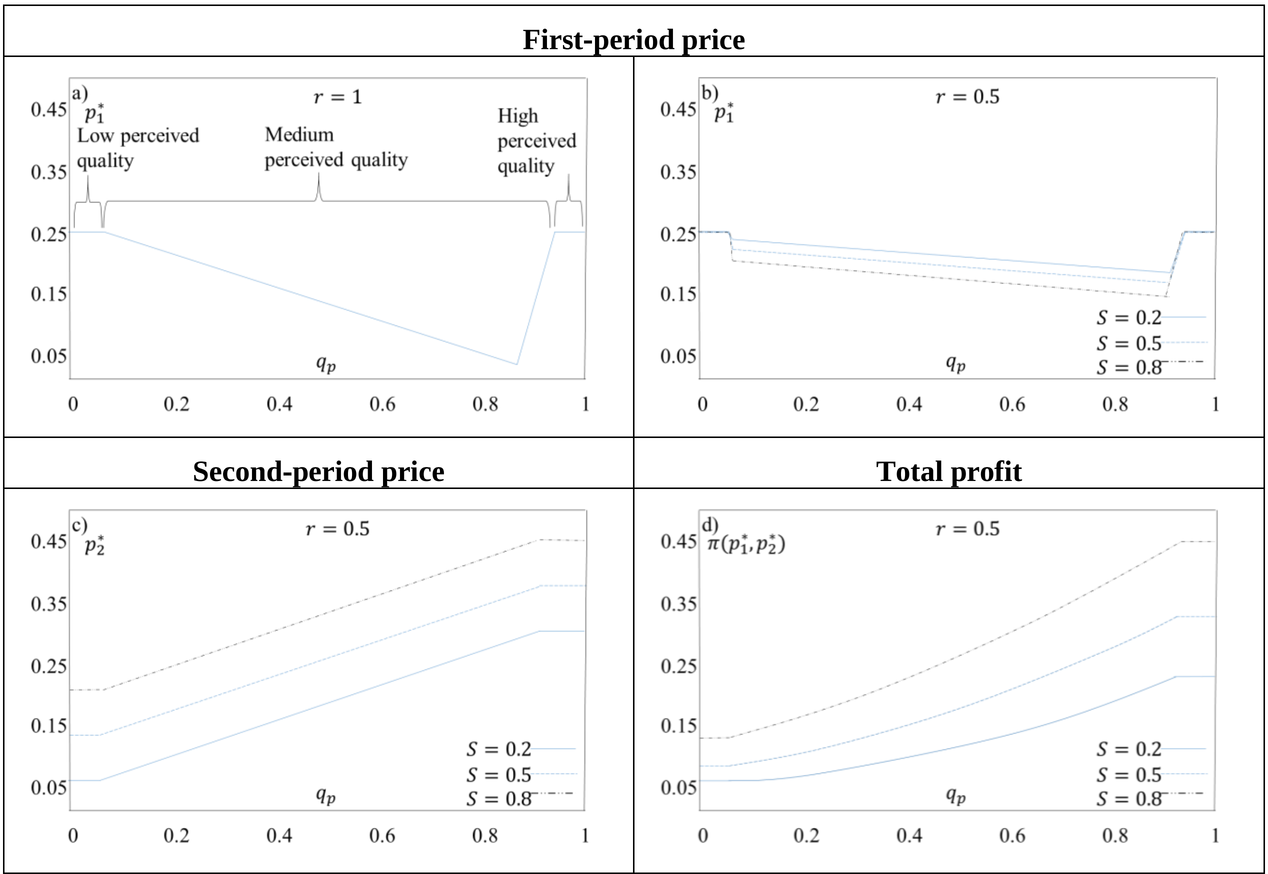


Figure 2. First- and Second-Period Optimal Prices and Total Profit for Different Values of r and S.

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.

Prediction 3: Second-period price p_2^* *increases with perceived quality* q_p $\left(\frac{\partial p_2^*}{\partial q_p} > 0 \text{ for } \overline{Q}_1 < q_p < max\left\{\overline{Q}_2, \frac{2}{2+b}\right\}\right)$. *The magnitude of this effect is increasing in* r.

Prediction 4: Second period price p_2^* *increases with an increasing additional quality signal* $\left(\frac{\partial p_2^*}{\partial S} > 0\right)$.

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 2 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.* $\left(\frac{\partial\left(\frac{\partial \pi(p_1^*, p_2^*)}{\partial S}\right)}{\partial q_p} > 0 \; for \; \overline{Q}_1 < q_p < max\left\{\overline{Q}_2, \frac{2}{2+b}\right\}\right)$.

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. Counterintuitively, a higher perceived quality is an incentive to invest even more in additional quality signals (see Figure 2, 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 Data

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.

Table 2: Summary Statistics

	Mean	Std. Dev.	Min	Max
Absolute price difference $(t_i - t_{i-1})$ in %	2.35	26.70	0	78.64
$PRICE$ (per night in $US)	178.05	299.59	9.95	10396.47
$CLEANING\_FEE$ (in $US)	43.63	53.75	0	1039.65
$EXTRA\_PEOPLE\_PRICE$ (in $US)	16.22	49.05	0	1874.07
$NUMBER\_OF\_PEOPLE$	3.25	2.13	1	16
$NUMBER\_OF\_BEDS$	1.72	1.21	1	16
$ENTIRE\_HOME$	0.57	0.50	0	1
$SHARED\_ROOM$	0.03	0.18	0	1
$PRIVATE\_ROOM$	0.40	0.49	0	1
$NUMBER\_OF\_REVIEWS$	21.60	39.18	0	868
$SUPERHOST$	0.18	0.39	0	1
$VERIFIED\_ID$	0.73	0.44	0	1
$OVERALL\_RATING$	4.77	0.34	1	5
$ACCURACY\_RATING$	4.84	0.30	1	5
$COMMUNICATION\_RATING$	4.91	0.23	1	5
$CLEANLINESS\_RATING$	4.76	0.38	1	5
$CHECK-IN\_RATING$	4.91	0.23	1	5
$LOCATION\_RATING$	4.78	0.34	1	5
$VALUE\_RATING$	4.74	0.33	1	5

Note: N= 143,405. Note that rating variables exist only for listings with at least three reviews. The absolute price difference reported in the first line is not a variable of our model but merely an additional piece of descriptive information.

The information incudes 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, presence of a superhost badge, and presence 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.

5 Hypotheses

In our empirical analysis, we focus on Prediction 4, for which we can operationalize the relevant variables based on our data. 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, while *superhost* is a badge that is relatively rarely obtained by hosts, a lot of them 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 awarded with a verified ID badge.

6 Empirical Analysis

First, we test our model assumption 3 regarding the relationship between prices and the overall rating as depicted in equation (1). To this end, we estimate a fixed effects model similarly to Li and Hitt (2010), regressing the overall rating of the current period on the natural logarithm of the price of the previous period.

Table 3: Results for Test of Assumption 3

	$OVERALL\_RATING$
LOG_PRICE_{t-1}	—0.02263***
	(0.01123)
$Constant$	1.98593***
	(0.75745)
Listing Fixed Effects	✓
Control Variables	✓
Observations	143,405
Within-R^2	0.166

Note: Robust standard errors clustered on the host level are in parentheses. *** p < 0.01; ** p < 0.05.

We control for the number of reviews, the other rating dimensions, the number of beds and people, and the room type. We cluster standard errors on the host level to account for the potential correlation between multiple listings managed by one host. The results depicted in Table 3 support our assumption 3 and suggest that an increase in the previous period price is correlated with a significant star decrease of 0.023 stars. 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.

To obtain a detailed estimation on how prices change in response to the three treatments in our hypotheses, we estimate a fully-flexible DiD model (see e.g., Autor (2003)), sometimes called relative time model (e.g., Burtch et al. 2018). We define three different treatments depending on whether (i) a listing's host has received the *superhost* badge, (ii) a listing's host has received the *verified ID* badge, or (iii) a listing has received one additional review. We incorporate listing and time fixed effects to account for time invariant unobservable heterogeneity, such as proximity to tourist attractions and temporal trends (e.g., seasonality). The coefficients of these interaction terms measure the average treatment effect on the treated (*ATT*) as long as the common trends assumption (CTA) (Angrist and Pischke 2008) holds. The major advantage of fully-flexible DiD models is that they directly allow for a test of the CTA by examining the existence of dissimilarities between treatment and control group in pre-treatment trends. Considering all treatments we have defined, we formulate the following model equation:

$$LOG\_PRICE_{it} = \alpha + \Sigma_j \beta_j (\mathrm{TREAT_i} * \mathrm{REL\_TIME}_{it}) + \beta_2 \tau_t + \beta_3 \gamma_{it} + \beta_4 \delta_i + \varepsilon_{it} \quad (8)$$

Our outcome variable is the natural logarithm of the current period price. 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/one more review(s) being received. The treatment effects are captured by all $\beta_j$after the treatment. The relative time period immediately before the treatment is omitted as the base case (e.g., as in Burtch et al. 2018) and a relative time period represents a time span of two weeks. τ is a vector of time dummies, γ is a vector of control variables consisting of number of reviews, number of beds, number of people, cleaning fee, price for extra people, and room type. δ is a vector of listing fixed effects and ε_{it} describes the remaining unobserved time-variant error term. Again, we cluster robust standard errors on the host level to account for hosts with multiple listings.

As depicted in Table 4, our results suggest that our estimation identifies a treatment effect of superhost badges (column (1)) and an extra review (column (3)), because no significant differences in pre-treatment trends are detected. The treatment coefficient for superhost badges indicates a significant price increase of 0.7% directly after the reception of the superhost badge. Thus, we find support for Hypothesis H2. For one more review (column (3), we find qualitatively the same results but the coefficient is smaller in magnitude (0.3%). Thus, we also find support for Hypothesis 1. After having received a verified ID badge (column (2)), hosts increase their prices by 1.1% on average, however, this price difference is also visible before receiving the treatment.

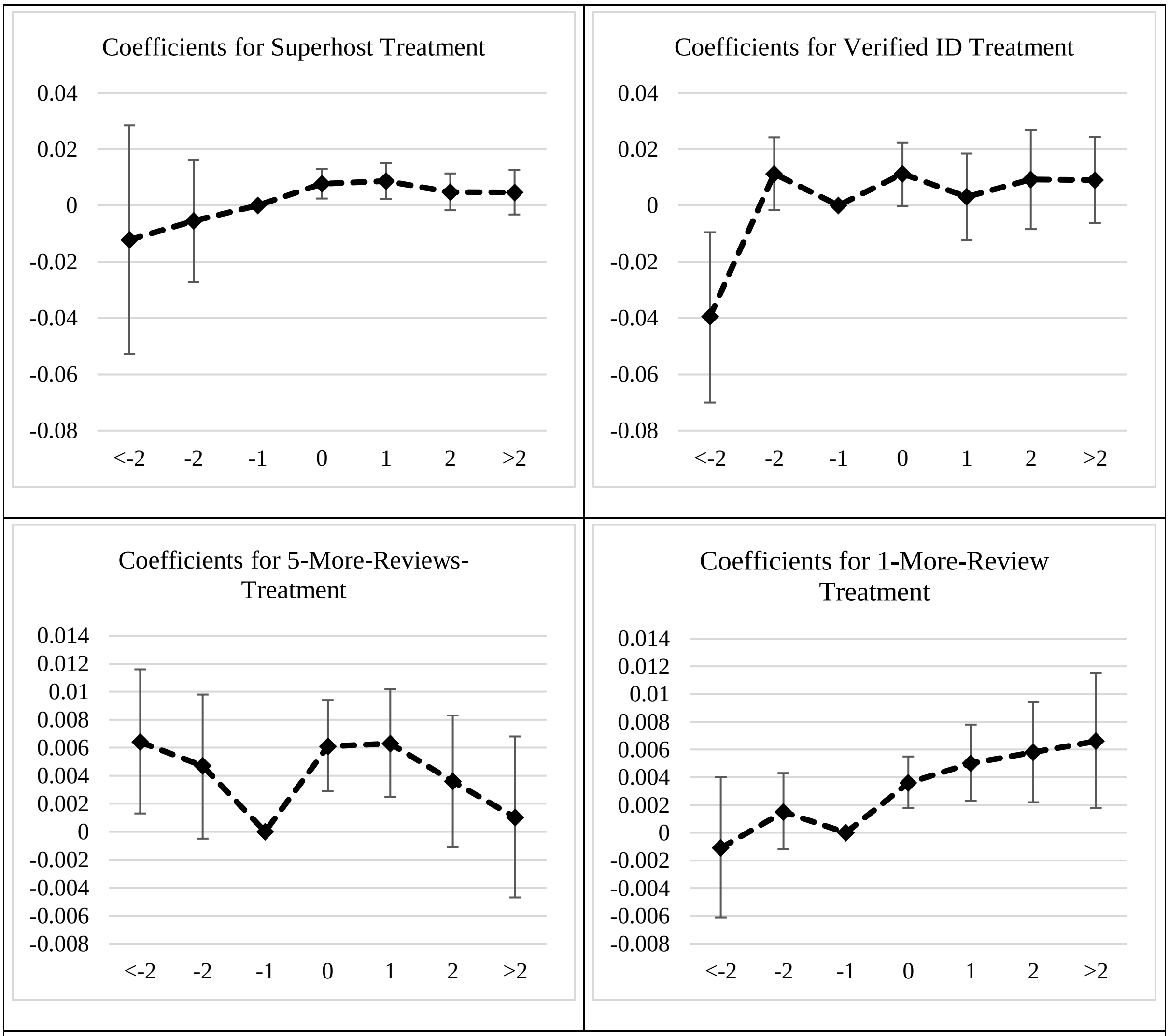
Table 4: Results of DiD-Estimations

	(1) Superhost Badge	(2) Verified ID	(3) 1 More Review
	$\boldsymbol{LOG\_PRICE}$	$\boldsymbol{LOG\_PRICE}$	$\boldsymbol{LOG\_PRICE}$
$TREAT_i * REL\_TIME_{i,>t-2}$	–0.01216 (0.02074)	–0.03949 (0.01531)	–0.00108 (0.00257)
$TREAT_i * REL\_TIME_{i,t-2}$	–0.00549 (0.01110)	0.01128* (0.00658)	0.00154 (0.00139)
$TREAT_i * REL\_TIME_{i,t-1}$	omitted	omitted	omitted
$TREAT_i * REL\_TIME_{i,t}$	**0.00774***** (0.002679)	**0.01125*** (0.00582)	**0.00365***** (0.00096)
$TREAT_i * REL\_TIME_{i,t+1}$	**0.00867***** (0.00323)	**0.00313** (0.00785)	**0.00503***** (0.00139)
$TREAT_i * REL\_TIME_{i,t+2}$	**0.00483** (0.00333)	**0.00931** (0.00903)	**0.00580***** (0.00185)
$TREAT_i * REL\_TIME_{i,t+3}$	**0.00472** (0.00402)	**0.00906** (0.00779)	**0.00664***** (0.00248)
$Constant$	4.58471*** (0.08091)	4.58459*** (0.08089)	4.58949*** (0.081116)
Control Variables	✓	✓	✓
Listing Fixed Effects	✓	✓	✓
Time Dummies	✓	✓	✓
Observations	143,405	143,405	143,405
Within R^2	0.0324	0.0338	0.0326

Note: Robust standard errors clustered on the host level are in parentheses. *** $p < 0.01$; ** $p < 0.05$.

This might be due to the fact that hosts know when they verify their ID, so they can raise their prices already before they actually complete the verification. Figure 3 provides a graphical representation of our coefficients, including the respective confidence intervals, with the relative time steps on the x-axis and depicts our results. These effects seem small, but 90% of absolute price changes are within a range of 0 to 1.92%. Therefore, our findings help explaining a substantial share of the observed variation in prices.

To conduct additional tests on 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 for model (1) and (3).



Note: The vertical axis displays the magnitude of the Treatment Coefficients from Table 4 and the horizontal axis displays the relative time periods from Table 4.

Figure 3. Treatments over Time

Interestingly, the results indicate that prior to being awarded a superhost badge, hosts on Airbnb slightly – though insignificantly – reduce their prices before and raise their prices directly after having received the badge. This result lends direct support our theoretical finding, that listing providers have an incentive to lower prices in the beginning (Prediction 1). Such a behavior is similar to the one described by the Ashenfelter-Dip (see Ashenfelter and Card (1985)). An explanation could be that hosts lower their prices to generate enough reservations in order to receive the superhost batch. This is in line with findings by Hui et al. (2016) who find that sellers on eBay reduce prices before a badge reevaluation. Interestingly, this also fits Prediction 2. However, the estimates for the other two treatments suggest that there is no clear effect for the verified ID badge and a strong fluctuation for the 5-more-review treatment. A reason for the former could be that the cost of achieving the verified ID badge is low and thus nearly all hosts have such a badge. As stated by Elfenbein et al. (2015), the value of certification is smaller if the certificate is relatively common.

7 Conclusion

Hosts in the sharing economy need to account for (i) interactions between prices and online ratings and (ii) a potentially inflated rating system, when determining optimal prices. Moreover, they can provide additional quality signals that consumers can use to infer the underlying quality of a product. As this has been widely neglected by previous research, our paper attempts to close this research gap and shed light on this pricing problem.

Consequently, to the best of our knowledge, this is the first study to propose a theoretical model 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, fully flexible DiD model.

Our work comes with important implications for research and practice. 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 (i.e., volume vs. valence).

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. Future research could extend these limitations, include a welfare analysis, or extend the time period studied to fully account for seasonal demand changes or special events that might drive demand.

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Appendix: Derivations of Optimal Prices, Optimal Profits, and Proofs

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:

$$\pi_2(p_2) = n\left(p_2 \cdot \frac{r \cdot \left(\max\{0, \min\{1, q_p - b(p_1 - d(q_p))\}\}\right) + (1-r) \cdot S - p_2}{t}\right) \tag{9}$$

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

$$\pi_2(p_2) = \begin{cases} np_2 \cdot \dfrac{r + (1-r)S - p_2}{t} \text{ if } 0 < p_1 < \dfrac{(2+b)q_p - 2}{2b} \\ np_2 \cdot \dfrac{\left(r\left(q_p - b\left(p_1 - \frac{q_p}{2}\right)\right) + (1-r)S - p_2\right)}{t} \text{ if} \dfrac{(2+b)q_p - 2}{2b} < p_1 < \dfrac{(2+b)q_p}{2b} \\ np_2 \cdot \dfrac{(1-r)S - p_2}{t} \text{ if } \dfrac{(2+b)q_p}{2b} < p_1 < q_e \end{cases} \tag{10}$$

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

$$p_2^*(p_1) = \begin{cases} \dfrac{S(1-r) + r}{2} \text{ if } 0 < p_1 < \dfrac{(2+b)q_p - 2}{2b} \\ \dfrac{S(1-r)}{2} + \dfrac{r\left((b+2)q_p - 2bp_1\right)}{4} \text{ if } \dfrac{(2+b)q_p - 2}{2b} < p_1 < \dfrac{(2+b)q_p}{2b} \\ \dfrac{S(1-r)}{2} \text{ if } \dfrac{(2+b)q_p}{2b} < p_1 < q_e \end{cases} \tag{11}$$

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

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

Total profit $\frac{p_1(q_e - p_1)}{t} + \pi_2^*(p_1)$ 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 $\overline{Q}_1$ and $\overline{Q}_2$) 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 $\overline{Q}_1$). 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 $q_p = \frac{bq_e+2}{b+2}$. Then, $\frac{q_e}{2} - p_1^* = 0$. Thus, $\frac{q_e}{2} - p_1^* > 0$ for smaller q_p. If $p_1^* = \frac{bnr\left((b+2)q_p r + S(1-r)\right) - 4q_e}{2b^2nr^2 - 8}$, it is maximal for $q_p = \frac{(1-r)\sqrt{4-b^2nr^2}S + bq_e r - 2S(1-r)}{(b+2)r}$. Then, $\frac{q_e}{2} - p_1^* = \frac{bnr(r-1)\sqrt{4-b^2nr^2}S}{2b^2nr^2-8} < 0$ since $n < \frac{4}{b^2r^2}$ in this case.

Proof of Prediction 2. $\frac{\partial \frac{bnr\left((b+2)q_p r + S(1-r)\right) - 4q_e}{2b^2nr^2-8}}{\partial S} = \frac{2bnr(r-1)}{2b^2nr^2-8} < 0$, since $n < \frac{4}{b^2r^2}$. *Proof of Prediction 3*. $\frac{\partial \frac{S(1-r)}{2} + \frac{r\left((b+2)q_p - 2bp_1^*\right)}{4}}{\partial q_p} = \frac{(b+2)r}{4} > 0$. *Proof of Prediction 4*. Denote the three solutions of p_2^* as O_1, O_2, O_3 respectively. Then, $\frac{\partial O_1}{\partial S} = \frac{\partial O_3}{\partial S} = \frac{1-r}{2} > 0$ and $\frac{\partial O_2}{\partial S} = \frac{1-r}{2} - \frac{2br\frac{\partial p_1^*}{\partial S}}{4} > 0$ since $\frac{\partial p_1^*}{\partial S} \leq 0$ (Prediction 2; for other cases of p_1^*: $\frac{\partial p_1^*}{\partial S} = 0$). *Proof of Prediction 5*. Since $\overline{Q}_1 < q_p < max\left\{\overline{Q}_2, \frac{2}{2+b}\right\}$, p_1^* is either 0 or $\frac{bnr\left((b+2)q_p r + S(1-r)\right) - 4q_e}{2b^2nr^2-8}$. Therefore, optimal second period profit $\pi_2^*(p_1)$ is equal to $\frac{n\left(br(q_p - 2p_1) + 2\left(q_p + S(1-r)\right)\right)^2}{16t}$ (see Equation12). Then $\pi^*(p_1) = \frac{p_1(q_e - p_1)}{t} + \frac{n\left(br(q_p-2p_1)+2\left(q_p+S(1-r)\right)\right)^2}{16t}$. If $p_1^* = \frac{bnr\left((b+2)q_p r + S(1-r)\right) - 4q_e}{2b^2nr^2-8}$, $\frac{\partial\left(\frac{\partial \pi(p_1^*)}{\partial S}\right)}{\partial q_p} = \frac{nr(b+2)(r-1)}{(b^2nr^2-4)t} > 0$, since $n < \frac{4}{b^2r^2}$ in this case. If $p_1^* = 0$, $\frac{\partial\left(\frac{\partial \pi(p_1^*)}{\partial S}\right)}{\partial q_p} = -\frac{nr(b+2)(r-1)}{4t} > 0$.