International Journal of Hospitality Management 99 (2021) 103065

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

The signaling and reputational effects of customer ratings on hotel revenues: Evidence from TripAdvisor

ATM Sayfuddin [a], Yong Chen [b,*]

[a] Department of Economics and Business, Randolph College, 2500 Rivermont Ave, Lynchburg VA 24503, USA

[b] Ecole hôtelière de Lausanne, HES-SO University of Applied Sciences Western Switzerland, Route de Cojonnex 18, 1000 Lausanne 25, Switzerland

ARTICLE INFO

Keywords:
Customer rating
Online review
Signaling effect
Reputational effect
TripAdvisor

ABSTRACT

This study aims to examine whether customer ratings and online reviews affect hotel revenues, and if so, to quantify the effects. To achieve this objective, we articulate the mechanisms grounded on reputation theories whereby customer ratings exercise the influence on hotel performance through reputational and signaling effects. Using customer rating data from TripAdvisor and hotel revenue data from Texas, we estimate fixed effects regressions and adopt a regression discontinuity design to separate the signaling effect of customer ratings from reputational effect. We found that the signaling effect of a 1-star increase is an increase of 2.2–3.0% in hotel monthly revenues whereas the reputational effect of a 1-star increase is an increase of around 1.5–2.3% in hotel monthly revenues. Our findings are robust across alternative model specifications and provide insightful implications for hotels to manage their customer ratings.

1. Introduction

The technological advancement in the twenty-first century has led to the digitization of interactions between firms and consumers on online platforms, where consumers post and share reviews about the products and services they have purchased or consumed. These online reviews, also known as user-generated content (UGC) or electronic word-of-mouth (eWOM), are indispensable for understanding consumption and production as the Internet becomes instrumental in facilitating transactions between consumers and firms. In recent years online reviews have been considered more effective in influencing consumer choice than traditional marketing and mass advertising (Gretzel and Yoo, 2008; Yang and Mai, 2010; Ye et al., 2011; Zhang et al., 2010). Conventional marketing that aims to inform customers about product quality and features has limitations due to high communication costs and low information credibility perceived by consumers. For instance, mass advertising is prohibitive whereas expert reviews, albeit informative, cannot cover large market segments. In this regard, online reviews play a crucial role in complementing traditional sources of information (Luca, 2016). However, online reviews are sometimes based on non-representative customer samples, hence subject to various biases in customer ratings (Hu et al., 2009; Li and Hitt, 2008). These biases impede prospective customers from deciphering the true quality of products and services.

There has been a growing strand of research on the influence of customer ratings and online reviews on firm performance. Zhu and Zhang (2010) found that online reviews affect the sales of video games, and in particular, concluded that online reviews are more influential for less popular games and games with more experienced players. Forman et al. (2008) reported that product sales on Amazon are positively associated with online reviews that contain identity-descriptive information of reviewers. Yang et al. (2018) synthesis of 25 studies in the tourism and hospitality industry reveals that hotel performance is affected by both customer rating scores and the number of online reviews. They also found that hotel performance is twice as much responsive to rating scores as to the number of online reviews. Phillips et al. (2015) found that online reviews are one of the determinants of hotel performance in Switzerland. Nieto-Garcia et al. (2019) found that hotel revenues are affected by different rating attributes such as staff and facilities.

While prior studies have provided plenty of evidence for the positive effect of customer ratings on firm performance (Luca, 2016; Yang et al., 2018), little is known about the mechanisms whereby firm performance is affected by customer ratings. In this regard, Jin and Leslie's studies (2003, 2009) showed that the financial performance of restaurants improves because the mandate disclosure of hygiene quality ratings helps

* Corresponding author.
E-mail addresses: asayfuddin@randolphcollege.edu (A. Sayfuddin), yong.chen@ehl.ch (Y. Chen).

https://doi.org/10.1016/j.ijhm.2021.103065
Received 31 December 2020; Received in revised form 24 August 2021; Accepted 27 August 2021
Available online 3 September 2021

diners to select high-rated restaurants while forcing low-rated restaurants to improve their hygiene quality. Namely, hygiene quality ratings along with the disclosure mandate increase restaurants' financial performance through reducing both adverse selection and moral hazard. If the mechanism in Jin and Leslie (2003, 2009) holds, customer ratings as a marked-based reputation system would affect hotel performance more than they do for restaurants. This is because asymmetric information is more pervasive in the hotel industry than in the restaurant industry. Not only do hotel guests need to take into account many factors in their booking, such as room amenities, hotel facilities, free breakfast and so forth, they are also from outside of town, which is not the case for restaurants whose customers are by and large localized.

This study aims to advance previous studies on the effect on customer ratings on firm performance in two ways. First, we aim to decompose the effect of customer ratings on firm performance into reputational effect and signaling effect that are grounded on reputation theories developed by Klein and Leffler (1981) and Shapiro (1982, 1983). In the context of customer ratings, reputation theories suggest that high customer ratings increase firm performance because they reduce moral hazard captured by reputational effect and preclude adverse selection captured by signaling effect. Second, insofar as empirical testing is concerned, we employ a quasi-experiment to isolate the signaling effect of customer ratings from the reputational effect, thereby estimating the magnitudes of the two effects on the one hand and lending empirical support to reputation theories on the other.

2. Literature review[1]

2.1. Customer ratings, reputation, and firm performance

The economic foundation for the mechanism that customer ratings affect firm performance can be traced back to reputation theories (Klein and Leffler, 1981; Shapiro, 1982, 1983). According to Shapiro (1983), reputation makes sense because consumers face imperfect information which precludes them from ascertaining quality provision of firms. In other words, if consumes have perfect information and hence can judge quality accurately, reputation will be negated in the market. A firm obtains a good reputation if consumers believe and expect, through learning or repeat purchases, that its product is of high quality (Shapiro, 1983). Klein and Leffler (1981) argue that firms produce high quality to earn reputation because the loss of reputation would do greater harm than the opportunistic benefits arising from cheating. Hence, reputation is endogenous in firm production, which rewards firms with repeat purchases and price premiums. Evidence has shown that reputation increases firms' financial returns through increasing consumers' willingness to pay for reputable firms (Dewan and Hsu, 2004; Houser and Wooders, 2006; Melnik and Alm, 2002; Resnick et al., 2006).

In digital marketplace, reputation is manifested as customer ratings or online reviews in the sense that customer ratings and reviews indicate firms' quality provision in the past as well as their commitment to high-quality provision in the future (Hollenbeck, 2018; Proserpio and Zervas, 2017; Zervas et al., 2021). It's not surprising that many studies verified a positive correlation between customer ratings and firm performance. To name a few, Xie et al. (2014) found that customer ratings are positively associated with revenues of hotels listed on TripAdvisor.com. Luca (2016) found that a 1-star increase in customer ratings on Yelp leads to an increase of 5–9% in restaurant revenues. Some studies have also shown that firms tend to perform better as the number of reviews increases, even though the aggregate customer ratings may remain unchanged (Chevalie and Mayzlin, 2006; Duan et al., 2008; Kim et al., 2016; Viglia et al., 2016; Zhu and Zhang, 2010). Torres et al. (2015) found that the number of online reviews has a positive effect on hotel booking on TripAdvisor. Tuominen (2011) verified the positive relationships between online review numbers and both hotel occupancy and RevPAR. Kim et al. (2015) found that online review numbers have a significant effect on hotel ADR and RevPAR.

2.2. Reputational effect

Klein and Leffler's (1981) model suggests that firms have incentives to build up reputation in the absence of government regulation in assuring quality. Klein and Leffler (1981) argue that market-enforced reputation mechanism that motivates traders to honor their promises is perhaps the cheapest way of guaranteeing quality. Even in perfectly competitive markets, reputable firms can reap positive economic benefits because they can attract repeat purchases and earn price premiums for high quality (Klein and Leffler, 1981). This is referred to as reputational effects, suggesting that reputation increases firm performance through reducing moral hazard on the supply side (Jin and Leslie, 2003, 2009; Klein and Leffler, 1981). Jin and Leslie (2009) is perhaps one of very few empirical studies that explicitly tested reputational effect by distinguishing between reputational and signaling effects which we shall address below. However, the reputational effect in their study is associated with restaurants' hygiene quality rated and discolored by government rather than voluntary customer ratings in digital market.

2.3. Signaling effect

On the demand side, reputation enables consumers to distinguish reputable firms from disreputable ones (Klein and Leffler, 1981; Shapiro, 1982, 1983). So long as consumers can make such distinction prior to purchase, reputable firms will attract prospective consumers while eventually driving out disreputable ones. That is, reputation reduces adverse selection through signaling high-quality provision (Jin and Leslie, 2003, 2009). In Klein and Leffler's (1981) model such signaling effects are exerted through reputable firms' identity-specific investment such as brand names, trademarks, and advertising that are identifiable in the market. In Shapiro's (1982, 1983) model, reputable firms can even signal high-quality provision by initially charging a low price and then recoup profits by charging price premiums for repeat purchases in subsequent periods. Since disreputable firms are unable to attract repeat purchases in the first place once consumers learn their low-quality provision, such low-price signal will not be emulated. Thus, it is in the best interest of disreputable firms to charge a high price and sell low quality when entering the market to rip consumers off. For this reason, the low-price signal ends up distinguishing reputable firms from disreputable ones, thereby reducing adverse selection.

In the theoretical models of reputation (Klein and Leffler, 1981; Shapiro, 1982, 1983), reputational and signaling effects are coherent and intertwined. Underlying reputation theories is the assumption that reputational signals perfectly reflect reputation on its own right and consumers can perfectly interpret reputation from these signals. Insofar as reputational signals are perfect and accurate, reputational and signaling effects are equal in affecting firm performance (Klein and Leffler, 1981). If a reputable firm cheats or defaults on high-quality provision, it will lose all identity-specific investment that are equal to its anticipated profit stream from repeat purchases (Klein and Leffler, 1981). Thus, reputational signals will still reflect the reputation of the firm, and signaling and reputable effects are the same. In cases where a reputable firm sells its reputation, say in the form of brand name, to another firm, signaling effects become exogenous and independent of reputational effects that the recipient firm has (Marvel and Ye, 2008; Tadelis, 1999, 2002, 2003). Other things being equal, the effect of transferred reputation on the performance of recipient firm, if any, will be the pure signaling effect.

[1] A table that summarizes the key studies of customer ratings and online review on firm performance can be found at the end of this paper (appendix).

2.4. Reputational and signaling effects of customer ratings

When it comes to customer ratings, Nieto-Garcia et al. (2019) argue that customer ratings are a heuristic tool for consumers to make a purchase, suggesting that customer ratings have a signaling effect. That is, other things being equal, consumers would choose high-rated firms, expecting high ratings to indicate high-quality provision. The signaling effect is also evidenced by the number of online reviews, because review numbers are not only a proxy of a large consumer base but perhaps an indication of the volume of repeat purchases (Luca, 2006; Yang et al., 2018). However, when customer ratings are distorted or biased in one way or another, they will derivate from firm reputation and hence cannot reflect reputation perfectly. Rating biases can be attributed to customers' rating behavior, in particular to a sort of network effects in which latter raters base their rating on early raters instead of their purchase experience (Eryarsoy and Piramuthu, 2014; Piramuthu et al., 2012; Sikora and Chauhan, 2012). It is also possible for firms to inflate rating scores through posting fake reviews (Luca and Zervas, 2016), and hence customer ratings will no longer reflect reputation at all. In both cases, the effect of customer ratings on firm performance, if at all, will be pure signaling effect of reputation.

Both reputational and signaling effects can minimize information asymmetry, thereby reducing moral hazard and adverse selection (Jin and Leslie, 2003, 2009). Reputable firms end up securing more businesses and charging price premiums, thereby outperforming their disreputable counterparts. However, many studies that tested the causality of customer ratings and firm performance is based on the assumption that customer ratings are endogenous to firm's high-quality provision and reputation. In other words, in these studies the effects of customer ratings on firms performance are reputational effects (Xie et al., 2014; Yang et al., 2018). Insofar as customer ratings are used as a measure of firm reputation, such reputational effects are more likely to be overestimated for at least two reasons. First, since customer ratings tend to be biased to high ratings (Li and Hitt, 2008; O'Connor and Cheema, 2018), this would inflate reputational effects. Second, the methods used by rating platforms, such as Yelp.com, to aggregate rating scores lead to changes in customer ratings that are irrelevant to firm reputation (Luca, 2016). Thus, part of customer rating scores are completely exogenous, and hence have no reputational effects.

3. Empirical context and the data

3.1. Online reviews on TripAdvisor.com

We selected TripAdvisor as the empirical context of this study for a couple of reasons. First, TripAdvisor is not only the pioneer of online travel intermediation but is also specialized in hotel booking. It is an early adopter of user-generated contents by providing various interactive forums which allow customers to post reviews and rate tourism products and services. A verified user can post reviews about his or her experience with various accommodation products, ranging from hotel, motel, bed and breakfast, to other vacation rentals. To post a review a user is required to register, free of charge, on TripAdvisor.com with a valid email address. Users can rate a hotel or a restaurant on a scale of 1 star to 5 stars in addition to posting a review about their experience with the hotel or restaurant as long as the reservation is made on TripAdvisor.com or through its mobile app. Anyone, with or without an account with TripAdvisor, can get access to reviews posted by other consumers and obtain a wide range of other publicly available information about hotels and restaurants that are listed on TripAdvisor.com. Besides online reviews, TripAdvisor records a wide array of information for registered hotels, including hotel amenities, address, hotel photos, awards and recognition, price range, and so on.

Second, for hotel managers TripAdvisor is usually the first point of call when it comes to online presence of their businesses (Xie et al., 2014). The website has been consistently ranked as the most popular website for hotel and restaurant booking in terms of the number of unique users in the U.S. (Statista, 2018). Unlike other leading travel websites (e.g., Expedia, hotels.com, booking.com, priceline.com, Travelocity.com, etc.) which distribute various travel products and services, including flights, taxis, and hotels, all at the same place, TripAdvisor is mainly a hotel intermediation and review site, and thus has accumulated rich data of online reviews on hotels (Frank, 2014). A recent study by ComScore reports that as many as 70% of the U.S. travelers visit TripAdvisor.com prior to booking a hotel. This study concludes that TripAdvisor is the most visited website and app by travelers in hotel booking based on an analysis of 325 similar websites in 12 major global markets, including the U.S. (TripAdvisor, 2018). These features enable us to test our research hypotheses more efficiently and thoroughly by taking the advantage of the large number of hotels registered on TripAdvisor as well as a rich set of information of online reviews, customer ratings, and hotel-specific characteristics.

3.2. Data description and aggregation

We focused on Texas of the U.S. because of the availability of crucial hotel revenue data in the state's public records. These data can be linked as much as possible to the online review data of TripAdvisor. The dependent variable of our interest is the monthly room revenues of hotels in Texas. We collected the revenue data from the Texas Comptroller of Public Accounts, which also contain information of hotel-specific characteristics, such as hotel name, address, and room numbers. For tax purposes, Texas law defines a hotel property as any building that is rented for sleeping accommodation for at least $15 per night. Thus Airbnb properties and many other vacation rentals which comply with the Texas tax code are also reported in the hotel revenue dataset. We only included hotel accommodations in the analysis. From TripAdvisor we collected data of online reviews and customer ratings in two stages. In the first stage, for all Texas hotels with active listings on TripAdvisor.com, we collected data of hotel name, address, amenities (e.g., free parking, shuttle service, pool, free breakfast, and so forth), as well as other hotel-specific information. In the second stage, we collected online review data, including review dates and review texts, for each hotel active on TripAdvisor.com during the period of this study. We matched the online review data with the hotel-specific data, particularly hotel revenues, to create the dataset for the analysis in this study.

Using hotel addresses, we combined hotel data from TripAdvisor.com with hotel revenue data from the Texas Comptroller of Public Accounts. One challenge in merging the two datasets was that the formats of addresses for many hotels differed in the datasets. We also identified multiple hotels with the same addresses, although this was rare in the datasets. To ensure that the two datasets were correctly merged, we utilized Python's FuzzyWuzzy package to match hotel names with their addresses. In this regard, we used an algorithm that produces a score of 0–100 to measure the extent to which two strings of words (or hotel names) match with each other. A score of 100 suggests a perfect match while a score of 0 suggests that hotel names do not match at all. After merging the datasets using hotel addresses, we extracted a subsample of hotels with a score of 100. In the final dataset, we identified 376,060 online reviews for 1348 distinct hotels, with their monthly taxable revenues available between January 2014 and December 2017. Table 1 reports the summary statistics of the online reviews and hotel revenues.

Table 1
Summary statistics of hotel revenues and customer rating.

Variable	N	Mean	Std. dev.	Min.	Max.
Hotel revenues (US$)	62,782	208,777	445,583	70	13,315,502
Customer ratings (star)	376,060	3.63	0.97	1	5
Review counts	376,060	4.00	7.88	0	196

Note: All statistics are per hotel per month in Texas.

The monthly hotel revenues in Texas averaged US$208,777 per hotel, and the customer ratings of hotels on TripAdvisor.com averaged 3.63 stars out of 5 stars. Also, each hotel received approximately 4 reviews on average per month on TripAdvisor.

Based on the customer rating data from TripAdvisor.com and the hotel revenue data from the Texas Comptroller Office, we present a preliminary description of the relationship between monthly hotel revenues and customer ratings. Fig. 1 illustrates the boxplots of the log revenues across different levels of star ratings for the 1348 hotels on TripAdvisor.com. First, the relationship between customer ratings and hotel revenues, if at all, is not monotonous in the whole range of customer ratings between 0 and 5 stars. Second, there appears a positive relationship between customer ratings and hotel revenues only for hotels with customer ratings between 3 stars and 4.5 stars. Third, as customer ratings exceed 4.5 stars, hotel revenues start to decrease with customer ratings. Further investigation also showed that hotels with a 5-star rating tended to have fewer customer ratings. We shall look into this preliminary finding in the result section of this study. Overall, it seems that hotel revenues are positively associated with customer ratings on a certain interval (between 3 stars and 4.5 stars). We proceed to model and explain why hotel revenues are positively associated with customer ratings on this interval, and thereby examine the signaling and reputational effects of customer ratings on hotel revenues.

4. Model specifications

One challenge in estimation of the empirical specifications was that the hotel revenue data are in monthly frequency, which is incomparable to customer ratings. To estimate the OLS regression we rounded customer ratings to obtain the monthly average rating of each hotel. We adopted two approaches to estimate the causal effect of customer ratings on hotel revenues. Using a fixed effects regression, we aimed to estimate the relationship between customer ratings and hotel revenues. Then we used a regression discontinuity specification in order to estimate the causal effect of customer ratings on hotel revenues and further to examine the signaling and reputational effects of customer ratings. For the regression discontinuity estimation, we assigned a treatment variable based on the following condition. If the customer rating of a hotel exceeds a threshold in a given month and stays above the threshold for at least half a month, we consider the hotel's rating as being above the discontinuity and otherwise below the discontinuity.

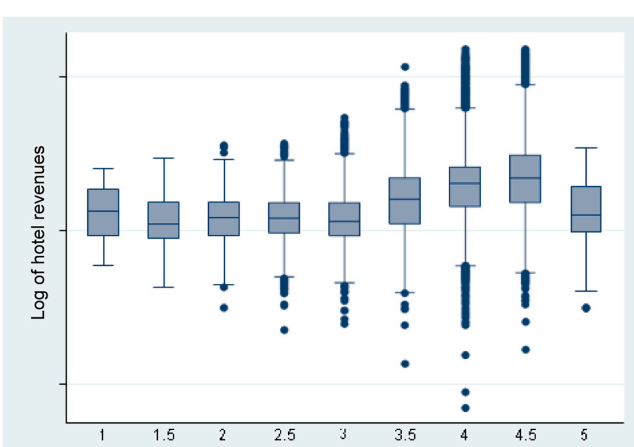

Fig. 1. Boxplot of hotel revenues at different star ratings. *Note*: On TripAdvisor each hotel is rated on a scale between 0 and 5 stars with an interval of 0.5 stars. TripAdvisor only displays the rounded average of customer ratings with a 0.5-star interval.

4.1. Fixed effect regression

In order to examine the relationship between customer ratings and hotel revenues, we first estimated a fixed effect regression with a model of hotel fixed effects. The empirical specification of the model is as follows:

$$\ln(Revenue_{it}) = \alpha rating_{it} + \theta_i + \delta_t + \epsilon_{it}, \quad (1)$$

where $\ln(Revenue_{it})$ denotes the log of hotel revenues of hotel i in month t; $rating_{it}$ denotes customer rating displayed on TripAdvisor for hotel i in month t; θ_i denotes time-invariant unobservables of hotel i, namely hotel fixed effects; and δ_t denotes time-variant unobservables, i.e., year and month fixed effects. The coefficient of interest is α, which, if statistically significant and positive, indicates that customer ratings have a positive impact on hotel revenues. However, it is also plausible that customer ratings are correlated with other unobservables that are associated with hotel revenues. To address this concern we used a regression discontinuity design which is addressed in detail below.

4.2. Regression discontinuity

The gold standard for estimating the causal relationship between two variables is an experimental design with randomized controlled trials (RCT), in which treated and control subjects are chosen randomly. Ideally in our study, an RCT would involve assigning customer ratings randomly (or exogenously) to hotels, allowing the researchers to estimate the true causal effect of customer ratings on hotel revenues. In reality though, designing an RCT is very difficult, if not impossible, depending on the research subject or context in which the study is curried out. However, in a highly rule-based world some rules can be rather arbitrary which not only provide good experiments closely mimicking an RCT but render empirical testing more feasible. For instance, in TripAdvisor's rating method, a customer rating is displayed as an average rating rounded to the nearest 0.5-star on a scale from 0 to 5 stars. Hence, any given TripAdvisor rating is either a rounded-up or rounded-down rating unless the actual customer rating happens to be an integer multiplied by a factor of 0.5 stars. Since the changes in customer ratings caused by rounding are irrelevant to the true reputation of hotels, TripAdvisor's rating method provides a natural experiment which enables us to use the quasi-experimental approach to decompose the effect of customer ratings on hotel revenues into signaling effect and reputational effect.

Consider two hotels *A* and *B*, with the actual ratings of 3.74 stars and 3.75 stars, respectively. TripAdvisor rounds *A*'s rating down to 3.5 stars while rounding *B*'s up to 4.0 stars. Given the fact that the actual ratings reflect the reputation of the two hotels, a decrease of 0.24 stars in *A*'s rating and an increase of 0.25 stars in *B*'s are completely independent of the reputation of the two hotels, and hence are exogenous. In the case above, *A*'s TripAdvisor rating 3.5 stars is a sum of a positive 3.74 stars accounted for by its reputation and thus suggesting the reputational effect and a negative 0.24 stars suggesting the signaling effect; *B*'s TripAdvisor rating 4.0 stars is a sum of a positive 3.75 stars accounted for by the reputational effect and a positive 0.25 stars accounted for by the signaling effect. Since the actual ratings of *A* and *B* are almost the same, they can be regarded as having the same reputation. Then, the difference in their revenues, if any, can only be attributed to the difference of 0.5 stars in their TripAdvisor ratings that is independent of their reputation, other things being equal. In other words, the signaling effect explains it all.

To estimate signaling effect of customer ratings, we used a sample of observations with underlying ratings within 0.1-star of the thresholds to compare the treated groups of hotels (rounded up) as opposed to the control group of hotels (rounded down). This allows us to estimate the average effect of an exogenous 0.5-star increase in TripAdvisor ratings on hotel revenues, namely the pure signaling effect of customer ratings.

We also used alternative bandwidths to estimate the pure signaling effect of customer ratings. In this regard, we adopted the following regression discontinuity approach to estimate the effect of a 0.5-star increase in TripAdvisor ratings on hotel revenues:

$$\ln(Revenue_{it}) = \beta T_{it} + \lambda r_{it} + \theta_i + \delta_t + \epsilon_{it}, \quad (2)$$

where $\ln(Revenue_{it})$ denotes the log of hotel revenues for hotel i in month t; T is a binary variable for the treatment of TripAdvisor rating, which takes the value of one if the actual customer rating for hotel i exceeds a threshold and, thus, is rounded up and zero otherwise. The coefficient of interest, β, indicates the discontinuous impact of moving from right below a threshold to above the threshold. That is, it measures the signaling effect of a 0.5-star increase in the TripAdvisor rating on hotel revenues that is not attributed to hotel reputation. Also, r_{it} denotes the underlying average rating of hotel i in month t, and hence coefficient λ indicates the reputational effect of customer ratings that is determined by hotel reputation. The model also controls for hotel-specific, time-invariant characteristics θ_i and time-variant unobservables δ_t as usual.

The main empirical specification incorporates a bandwidth of 0.1 stars to include only the observations that are up to 0.1-star away, in terms of their underlying average ratings, from the rounding threshold. To demonstrate that the results are not driven by the choice of the bandwidth and hence are independent of it, we used alternative bandwidths, as illustrated in Section 5.2 (see Table 4). We also allowed for potential non-linear responses to customer ratings by including quadratic and higher order ratings in model estimation.

4.3. Heterogeneous impacts

After examining the effect of customer ratings on hotel revenues, we examined whether the magnitude of the effect changes with the number of online reviews for hotels on TripAdvisor. The rationale for conducting this analysis is that if each online review contains noisy information related to the reputation of a hotel, customer ratings as a signal would become less noisy and more informative as more online reviews are posted for the hotel, and hence better reflect the reputation of the hotel. If more online reviews indeed translate to more precise information of hotel reputation, customer ratings presumably have increasingly greater impacts on hotel revenues as the number of online reviews increases. To test this hypothesis we use the following empirical specification:

$$\ln(Revenue_{it}) = \alpha rating_{it} + \beta reviews_{it} + \gamma rating_{it} * reviews_{it} + \theta_i + \delta_t + \epsilon_{it}, (2)$$

where $\ln(Revenue_{it})$ denotes the log of hotel revenues for hotel i in month t; $rating_{it}$ denotes TripAdvisor rating for hotel i in month t as in Eq. (1); $reviews_{it}$ denotes dummy variables for different bins of review counts (i.e., 0–10, 11–20, 21–30, 31–40, 41–50, and 50+ reviews) posted for hotel i in month t; and the interaction term, $rating_{it} * reviews_{it}$, is of our primary interest as it captures the interactions between customer ratings and the number of online reviews. Equation (3) is a modification of Eq. (1) by incorporating the interaction term $rating_{it} * reviews_{it}$ in the model. As usual, θ_i denotes time-invariant unobservables of hotel i, and δ_t denotes time-variant unobservables.

5. Results and discussion

5.1. Fixed effects estimates

Table 2 reports the results for the fixed effects regression specified in Eq. (1). The result shows that a 1-star increase in TripAdvisor ratings is associated with a 4.5% increase in hotel revenues on average after controlling for the hotel-specific characteristics and time-variant observables. This result suggests a positive correlation between customer ratings and the performance of hotels listed on TripAdvisor. Referring to previous research, we conclude that customer ratings and hotel performance are by and large positively correlated as verified in many studies that addressed the effects of customer ratings in different business contexts. Two questions remain though. First, from a theoretical point of view, we have not yet examined whether the positive effect of customer ratings on hotel revenues is due to the signaling effect or reputational effect, or even both. Eq. (1) does not allow us to make such a distinction. Second, one limitation of this empirical specification is that customer ratings may be correlated with other unobservable changes in hotel reputation that are not modeled in the equation. Hence the estimated coefficient of customer ratings in Table 2 could be biased due to the unobserved factors that are correlated to customer ratings on TripAdvisor.

Table 2
Effects of customer ratings on hotel revenues.

Independent variable	Coefficient (α)
Customer ratings	0.045***(0.002)
Monthly fixed effects	Yes
Hotel fixed effects	Yes
Observations	62,782
Number of hotels	1348

Note: Dependent variable: ln(*Revenue*). Robust standard errors are reported in parenthesis. *, **, ** indicate significance at 10%, 5%, and 1% level, respectively.

5.2. Regression discontinuity estimates

Because the fixed effect regression does not account for the potential unobserved variables that are correlated to TripAdvisor rating, this model could produce biased estimates for the effect of customer ratings on hotel revenues. To address this concern, we adopted regression discontinuity as an alternative specification in Eq. (2). Table 3 presents the regression discontinuity estimates of the effect of a 0.5-star increase in customer ratings on hotel revenues. The results show that a discontinuous jump of a 0.5-star increase in customer rating leads to a 1.1% increase in hotel revenues as shown in column (1). The estimated effect remains unchanged when we include quadratic ratings shown in column 2 and higher order ratings in column 3. These results have two profound implications for unraveling the mechanisms of customer ratings on hotel performance. First, they lend further support to the argument that hotel performance is positively affected by customer ratings. Second, most importantly, the results suggest that the increase in hotel revenues by 1.1% can be entirely attributed to the signaling effect of customer ratings instead of the reputational effect. This is because the increase of a 0.5-star in customer ratings on TripAdvisor is independent of the reputation of hotels (Table 4).

There are two explanations for signaling effect of customer ratings on hotel performance. First, higher customer ratings immediately reduce adverse selection of consumers despite the fact that high TripAdvisor

Table 3
Regression discontinuity estimates of customer ratings.

Independent variable	Coefficient (β)		
	(1)	(2)	(3)
Discontinuity	0.011** (0.005)	0.011** (0.005)	0.011** (0.005)
Customer ratings	Yes	Yes	Yes
Rating quadratic		Yes	
Rating high order			Yes
Monthly fixed effects	Yes	Yes	Yes
Hotel fixed effects	Yes	Yes	Yes
Observations	25,085	25,085	25,085
Number of hotels	1140	1140	1140

Note: Dependent variable: ln(*Revenue*). Regressions include all observations within 0.1 stars of a discontinuity. Robust standard errors are reported in parenthesis. *, **, ** indicate significance at 10%, 5%, and 1% level, respectively.

Table 4
Regression discontinuity for different bandwidths.

Independent variable	Coefficient (β)	
	(1)	(2)
Discontinuity	0.011**	0.015***
	(0.005)	(0.004)
Customer ratings	Yes	Yes
Monthly fixed effects	Yes	Yes
Hotel fixed effects	Yes	Yes
Observations	25,085	12,636
Number of hotels	1140	939
Bandwidths (stars)	0.2	0.1

Note: Dependent variable: ln(*Revenue*). Column 1 and 2 report the estimates of regression discontinuity models with 0.2 and 0.1 bandwidths, respectively. Robust standard errors are reported in parenthesis. *, **, ** indicate significance at 10%, 5%, and 1% level, respectively.

ratings are not entirely grounded on the reputation of hotels. An increase of a 0.5-star in customer ratings around the threshold is sufficient to entice consumers to book highly-rated hotels in the short run, thereby boosting hotel revenues. Second, hotels are incentivized to increase service quality to a level that allows them to obtain a rating just right above the threshold provided that hotel managers are well aware of TripAdvisor's rounding method. This helps to reduce moral hazard of hotels as well. As long as the actual rating of a hotel exceeds the threshold, it ends up with a 0.5-star rise in its TripAdvisor rating, and hence distinguishes from its competitors right below the threshold. Unlike Jin and Leslie (2003, 2009), our study shows that moral hazard is reduced to an extent that allows customer ratings to pass the threshold. This perhaps explains why hotels obtaining more than 4.5 stars have no such incentives, whereby customer ratings would reflect the reputation of hotels in the long run.

To graphically illustrate the discontinuous relationship between customer ratings and hotel revenues, we demeaned each hotel's log revenue to normalize it to zero. Then we construct a range of bins of customer ratings of hotels based on the distance of the actual ratings from the rounding thresholds. We take the average of log revenue at different bins to plot the average log revenues as a function of customer ratings. Fig. 2 provides a graphical illustration of the demeaned revenues for hotels right above and below the rounding thresholds. In this figure, zero (0) is the normalized, rounding threshold after which we see a discontinuous jump of log revenue, suggesting a causal effect of customer ratings on hotel revenues.

Table 4 reports the regression discontinuity estimates for different bandwidths. Columns 1 and 2 show the results for the bandwidths of 0.2 stars and 0.1 stars, respectively, around the rounding thresholds. When the bandwidth changes from the original bandwidth of 0.2 stars to 0.1 stars, we find that a 0.5-star increase in customer ratings leads to a 1.5% increase in monthly hotel revenues. A hotel's reputation should be independent of whether the hotel's average customer rating is rounded up or down. The regression discontinuity results thus lend support to the hypothesis that customer ratings have a causal effect on hotel revenues, and this effect is the signaling effect insofar as the rounding method is used. The signaling effect is irrelevant to the reputation of hotels listed on TripAdvisor. We therefore successfully decoupled the signaling effect from the reputational effect. According to Tables 2–4, the signaling effect of a 1-star increase is an increase of 2.2–3.0% in hotel monthly revenues whereas the reputational effect of a 1-star increase is an increase of around 1.5–2.3% in hotel monthly revenues.

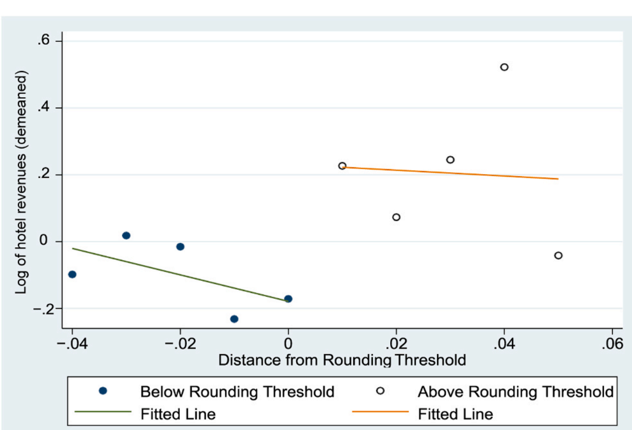

Fig. 2. Average hotel revenues around discontinuity of customer ratings.

5.3. Heterogeneous impacts

Based on equation 3, Table 5 presents the results for the heterogeneous impacts of customer ratings on hotel revenues by factoring in the number of online reviews in a given period of time. If each online review contains noisy information about the true reputation of a hotel, the information of customer ratings will become more accurate as the number of reviews increases. In other words, the more online reviews a hotel receives, the more accurately its customer rating will reflect its reputation. Hence the effect of customer ratings on hotel revenues would increase with the number of online reviews. Table 5 shows that the coefficient of customer ratings strictly increases with the number of online reviews, suggesting that the number of online reviews reinforces the effect of customer ratings. Relative to the hotels with 10 or fewer reviews, a 1-star increase in customer ratings leads to an increase of 3.5% in revenues of hotels with over 50 reviews while only an increase of 1.6% in revenues of hotels with 20 or fewer reviews. This result suggests that the reputational effect of customer ratings intensifies perhaps because online reviews reduce information noise of reputation.

6. Robustness check

6.1. Review manipulation

We proceed to conduct a few robustness checks. One concern in the regression discontinuity approach is that the underlying average ratings could also be known to hotel managers. This leaves potentials for manipulation of customer ratings, as pointed out by McCrary (2008). Hotel managers could post fake reviews to inflate their hotel ratings, which would boost their revenues in the short run. It is also possible that certain hotels, such as hotels that earn unusually high or low revenues,

Table 5
Heterogeneous impacts of customer ratings.

Independent variables	Coefficient (γ)
Customer ratings	0.042***
	(0.002)
Rating × (11–20 reviews)	0.016**
	(0.007)
Rating × (21–30 reviews)	0.017**
	(0.008)
Rating × (31–40 reviews)	0.027*
	(0.014)
Rating × (41–50 reviews)	0.029**
	(0.008)
Rating × (50+ reviews)	0.035**
	(0.015)
Monthly fixed effects	Yes
Hotel fixed effects	Yes
Observations	62,782
Number of hotels	1348

Note: Dependent variable: ln(*Revenue*). Robust standard errors are reported in parenthesis. *, **, ** indicate significance at 10%, 5%, and 1% level, respectively.

are susceptible to manipulating their ratings. In such cases, the regression discontinuity results could be spurious. In this section, we provide statistical evidence that rules out the possibility of review manipulation, thereby confirming the reputational incentive of customer ratings. If a hotel submits fake or inflated reviews to manipulate its rating, it would stop submitting reviews once the rating exceeds a rounding threshold. However, if it stops submitting reviews immediately after jumping above the discontinuity, a subsequent negative review from a customer will then bring back the rounded rating below the discontinuity. The hotel, therefore, needs to continue submitting positive reviews to increase its rating to a level that is sufficiently above the discontinuity (for instance, from 3.2 stars to 3.4 stars). This ensures that the rounded rating would not be easily brought down and below the discontinuity. While the degree of manipulation is hard to predict and measure, it is a fairly restrictive type of manipulation for the regression results to be spurious.

We conducted a statistical test provided by McCrary (2008), showing no evidence for manipulation of customer ratings on hotels' side insofar as the manipulation is related to surpassing the threshold. This test is based on the idea that if a hotel fabricated reviews on TripAdvisor for inflating its rating, there would be a disproportionately large number of reviews just right above the rounding thresholds. To test this hypothesis, the number of online reviews and TripAdvisor's underlying customer ratings are the two variables of our interest. First, we sum the number of reviews for each 0.05-star interval of underlying rating and calculate the probability mass for every interval. Second, we construct a dummy variable that measures the intervals that are right above the discontinuity (i.e., 2.25–2.30 stars, 2.75–2.80 stars). This test utilizes the probability mass, from the first step, as the dependent variable and the dummy variable, from the second step, as the independent variable. Table 6 shows that the number of reviews right above the discontinuity is not statistically different or significantly high. Thus the manipulation of reviews by hotels would not be a concern for the regression discontinuity approach.

6.2. Other robustness checks

Another concern is that customer ratings on TripAdvisor are supposed to have a direct effect on the number of online booking (or revenue from booking via TripAdvisor) rather than on hotel revenues. After checking various hotels, hotel amenities, and online reviews at a destination of interest, a guest could book a hotel far ahead of his date of arrival at a hotel. Guests are usually required to provide their credit card information for securing booking while making payment at a later date, usually during or after their hotel stay. This ends up with a time-lapse between booking and payment. Therefore, the number of online bookings, instead of monthly hotel revenues, is supposed to be more directly affected by discontinuous changes in customer ratings of hotels. In addition, monthly hotel revenues as a proxy for online hotel booking may be somewhat noisy because they include revenues earned from bookings that are made in the same month as well as in preceding months. Because of the unavailability of information regarding the exact date that each guest makes a reservation, the effect of customer ratings on hotel revenues may be underestimated in this study. We attempt to address this concern below.

Table 6
McCrary Test for random reviews.

Test	
Treatment (0.05-star interval above rounding thresholds)	-0.0009
	(0.0007)
Observations	79

Note: Dependent variable is the probability mass of reviews on each 0.05-star interval. The treatment variable represents intervals right above a rounding threshold.

TripAdvisor (2018) reports that 84% of their customers book hotels through the site within the same month of arrival at a hotel. This leaves only 16% of hotel guests making reservations at least one month prior to their hotel stay. Therefore, the bias of using monthly hotel revenues as the identification strategy in this study, if any, is very limited. We have conducted further robustness check using quarterly revenue data and estimated the same regression discontinuity model in Eq. (2). Table 7 shows that the signaling effect of a 0.5-star increase in customer ratings on quarterly hotel revenues is the same as what we found with the monthly revenue data shown in Table 3. The regression discontinuity estimate using both the monthly and quarterly hotel revenue data suggests that a 1.1% increase in hotel revenues is attributed to every 0.5-star increase in hotel ratings displayed on TripAdvisor. Therefore, we can confirm that the effect of customer ratings on hotel performance is relabel and stable.

7. Conclusion

7.1. Theoretical implications

This study has advanced previous studies on customer ratings by isolating signaling effect from reputational effect on firm performance. Unlike previous studies that treated customer ratings as an explanatory variable no different from other determinants of firm performance, we grounded the effect of customer ratings on reputation theories, which allowed us to articulate the signaling and reputational effect of customer ratings. The classification of the two effects is a theoretical imperative to examine the mechanisms by which customer ratings affect hotel performance in the first place. Because of a lack of understanding of such mechanisms, not only is the empirical evidence for the effect of customer ratings dubious but the interpretation of the evidence is far from convincing. To empirically disentangle the two effects we used a regression discontinuity design that fits well with TripAdvisor's rating method. The regression discontinuity is by far the most effective method for this purpose since TripAdvisor artificially creates thresholds of customer ratings for each 0.5-star interval. While two hotels may be indistinguishable in terms of their actual ratings that suggest the same reputation, ratings below and above a threshold will end up with a discrepancy of as much as 0.5 stars in their ratings on TripAdvisor.

In this regard, this study provides compelling evidence for the financial implications of customer ratings on TripAdvisor. We found that an exogenous 1-star increase in TripAdvisor rating leads to an increase of 2.2–3.0% in hotel monthly revenue. For an average hotel in Texas, this signaling effect is equivalent to an additional monthly revenue of US $4593–US$6263 or yearly revenue of US$55,117–US$75,159. This effect is robust across different bandwidths of customer ratings. This study also lends support to the interaction of online reviews and customer ratings on hotel performance. For instance, hotels obtaining more than 50 reviews outperform those obtaining 10 or fewer reviews by 3.5% in monthly revenues. We have also addressed the concern associated with guests booking hotels at least one month before their dates of arrival,

Table 7
Regression discontinuity estimate using quarterly revenue data.

Independent variable	Coefficient (β)
Discontinuity	0.011***
	(0.004)
Customer ratings	x
Monthly fixed effects	Yes
Hotel fixed effects	Yes
Observations	9502
Number of hotels	1141

Note: Dependent variable: ln(*Revenue*). Robust standard errors are reported within parenthesis. *, **, *** denote significance at the 10%, 5%, and 1% level.

which could bias the regression results due to the use of monthly revenue data. However, by estimating the regression discontinuity model using the quarterly revenue data, we found no changes in the regression discontinuity results. Overall, this study contributes to the literature of online reputation and firm performance and provides a quantitative measure for the impact of TripAdvisor ratings on hotel revenues.

7.2. Managerial implications

The rising importance of online reputation poses both opportunities for and perhaps threats to hotel managers. Having full control over the asset of online reputation is often a challenging task for every business manager, including hotelier, as it is by no means easy to convert reputation, an intangible asset, into monetary value of firms (Roos et al., 2005). According to Castro et al. (2004), information management is a cornerstone for building up corporate reputation, which requires dynamic information management and a smooth communication channel between businesses and customers. Online reviews and customer ratings are a crucial source of information that can shape the reputation of tourism businesses. We found no evidence that hotels manipulated their customer ratings by taking the advantage of TripAdvisor's rating method to inflate the reputational signal. However, such manipulation cannot be ruled out on other platforms where hotels could sabotage the rating system. When this happens, the causal effect of customer ratings on hotel performance would completely, if not immediately, disappear because customers ratings will no long reflect the reputation of hotels nor are they effective in separating reputable hotels from the disreputable.

7.3. Limitations and future research

There are a couple of limitations as well as future research directions worth noting. First, customer ratings only address one aspect of firm reputation, namely customer evaluation of firm reputation based on their purchase experience. Yet reputational theories suggest that reputation can be evidenced by all firm-specific nonsalvageable assets, such as brand names, advertising and so on. Future research could take a supply perspective to measure reputation in order to obtain a fuller picture of reputational effect on firm performance. Besides, it would be insightful if future research could test reputational effects associated with different reputation measures as well as their interactions in affecting firm performance. Second, the signaling effect we tested was restricted to the threshold of customer ratings on TripAdvisor. Future research could test the signaling effect on other platforms where different aggregating methods or rating schemes are used. This would enrich the findings in this line of research. Third, we suggest comparing voluntary customer ratings such as in this study and rating disclosure mandated by government such as in Jin and Leslie's studies (2003, 2009). The reputational and signaling effects could be different across these two ratings schemes.

Appendix

Key studies on customer ratings and online reviews on firm performance.

Authors	Major research question (s)	Estimation approach	Platform	Industry	Major findings
Duan et al. (2008)	EWOM on box office performance	Simultaneous equations	Variety.com, Yahoo! Movies, etc.	Movie	Box office revenue and WOM valence influence WOM volume; WOM volume leads to higher box office performance
Forman et al. (2008)	Reviewers' disclosure of identity information on purchase decision	Fixed effects panel regressions	Aamazon.com	E-commerce	Online reviews containing identity-descriptive information are rated more positively, and the availability of reviewers' identity information is associated with subsequent sales
Gretzel, Yoo (2008)	Travelers' reviews on trip planning	Web-based survey	TripAdvisor.com	Travel and tourism	Reviews are mostly used for making accommodation decisions and not much for en route travel planning.
Kim et al. (2016)	Online reviews on financial performance of restaurants	Correlation analysis	TripAdvisor.com, Yelp.com, etc.	Restaurant	The number of online reviews is positively associated with restaurant performance. The relationship between review numbers and restaurant performance is moderated by excellence certificates
Luca (2016)	Whether online consumer reviews affect restaurant demand	Fixed effects regressions	Yelp.com	Restaurant	A one-star improvement of online rating increases revenue by 5–9%. Independent restaurants are the main beneficiaries of online ratings
Nieto-Garcia et al. (2019)	weight of each hotel-rating attribute in terms of revenue maximization	Multi-criteria decision analysis	Booking.com	Hotel	Staff and facilities are central attributes affecting hotel RevPAR
Phillips et al. (2015)	Relationships among online reviews, hotel characteristics, and revpar	Artificial neural network analysis	Semantic search engine	Hotel	Room quality, positive regional review, and hotel reputation have negative impacts on RevPAR, while regional room star rating has a positive impact
Torres et al. (2015)	Financial impact of hotel reviews and ratings on online transactions	Multiple regression analysis	TripAdvisor.com	Hotel	TripAdvisor ratings and reviews are positively associated with online booking transactions
Tuominen (2011)	Travel reviews and ratings on hotel performance	Correlation analysis	TripAdvisor.com	Hotel	Hotel reviews and ratings are associated with hotel performance
Viglia et al. (2016)	Online reviews on hotel occupancy	Regression analyses and associations	Booking.com, TripAdvisor.com, and Venere.com	Hotel	Review scores are positively associated with occupancy. The number of reviews positively affect occupancy with diminishing returns.
Xie et al. (2014)	Business value of online reviews and management response	Associations or correlations	TripAdvisor.com	Hotel	Overall ratings, management responses, and variation and volume of customer reviews are significantly associated with hotel performance
Yang and Mai (2010)	Online reviews on video game sales	Multiple regression analysis	Gamespot.com	Video game	Customer experiences shared through online reviews do not fully transform experience attributes into search

(continued on next page)

(*continued*)

Authors	Major research question (s)	Estimation approach	Platform	Industry	Major findings
					attributes; negative reviews have greater impacts than positive reviews
Yang et al. (2018)	Relationship between eWOM and hotel performance	Hierarchical linear model	Multiple platforms	Tourism and hospitality	Average eWOM valence-based elasticity is 0.888, and the average volume-based elasticity is 0.055.[a]
Ye et al. (2009)	Online reviews on hotel sales	Fixed effects regressions	Ctrip.com	Hotel	Significant relationship between online reviews and hotel performance.
Ye et al. (2011)	Online reviews on hotel sales	Multiple regressions	Ctrip.com	Hotel	A 10% increase in traveler review increases online sales by greater than 5%.
Zhang et al. (2010)	Mechanism for consumers to judge the persuasiveness of online reviews	ANOVA, binary logit model	Amazon.com	E-commerce	When evaluating products with promotion goals, consumers perceive positive reviews to be more persuasive; when evaluating products with prevention goals, they perceive negative reviews to be more persuasive
Zhu and Zhang (2010)	Online reviews on sales moderated by product and customer characteristics	Difference in differences (DID)	NPD Group	Video game	Online reviews have greater influence for less popular games and for games played by players with more internet experience

[a]eWOM elasticity refers to percentage changes of firm performance against percent changes of eWOM consisting of valances and volumes of review ratings.

References

Castro, G., Saez, P., Lopez, J., 2004. The role of corporate reputation in developing relational capital. J. Intellect. Cap. 5 (4), 575–585.

Chevalie, J.A., Mayzlin, D., 2006. The effect of word of mouth on sales: online book reviews. J. Mark. Res. 43 (3), 345–354.

Dewan, S., Hsu, V., 2004. Adverse selection in electronic markets: evidence from online stamp auctions. J. Ind. Econ. 52 (4), 497–516.

Duan, W., Gu, B., Whinston, A.B., 2008. The dynamics of online word-of-mouth and product sales—an empirical investigation of the movie industry. J. Retail. 84 (2), 233–242.

Eryarsoy, E., Piramuthu, S., 2014. Experimental evaluation of sequential bias in online customer reviews. Inf. Manag. 51 (8), 964–971.

Forman, C., Ghose, A., Wiesenfeld, B., 2008. Examining the relationship between reviews and sales: the role of reviewer identity disclosure in electronic markets. Inf. Syst. Res. 19 (3), 291–313.

Frank, B.H., 2014. World's largest travel site? Expedia and TripAdvisor Both Lay Claim to Title. ⟨https://www.geekwire.com/2014/heres-expedia-can-claim-worlds-largest-online-travel-agency/⟩. (Accessed 15 December 2018).

Gretzel, U., Yoo, K.H., 2008. Use and impact of online travel reviews. In: O'Connor, P., Höpken, W., Gretzel, U. (Eds.), Information and Communication Technologies in Tourism 2008. Springer, Vienna, pp. 35–46.

Hollenbeck, B., 2018. Online reputation mechanisms and the decreasing value of chain affiliation. J. Mark. Res. 55 (5), 636–654.

Houser, D., Wooders, J., 2006. Reputation in auctions: theory, and evidence from eBay. J. Econ. Manag. Strategy 15 (2), 353–369.

Hu, N., Zhang, J., Pavlou, P.A., 2009. Overcoming the J-shaped distribution of product reviews. Commun. ACM 52 (10), 144–147.

Jin, G.Z., Leslie, P., 2003. The effect of information on product quality: evidence from restaurant hygiene grade cards. Q. J. Econ. 118 (2), 409–451.

Jin, G.Z., Leslie, P., 2009. Reputational incentives for restaurant hygiene. Am. Econ. J. Microecon. 1 (1), 237–267.

Kim, W.G., Li, J., Brymer, R.A., 2016. The impact of social media reviews on restaurant performance: the moderating role of excellence certificate. Int. J. Hosp. Manag. 55, 41–51.

Kim, W.G., Lim, H., Brymer, R.A., 2015. The effectiveness of managing social media on hotel performance. Int. J. Hosp. Manag. 44, 165–171.

Klein, B., Leffler, K.B., 1981. The role of market forces in assuring contractual performance. J. Political Econ. 89 (4), 615–641.

Li, X., Hitt, L.M., 2008. Self-selection and information role of online product reviews. Inf. Syst. Res. 19 (4), 456–474.

Luca, M., 2016. Reviews, Reputation, and Revenue: the Case of Yelp.com. Harvard Business School NOM Unit Working Paper, 12-016.

Luca, M., Zervas, G., 2016. Fake it till you make it: reputation, competition, and Yelp review fraud. Manag. Sci. 62 (12), 3412–3427.

Marvel, H.P., Ye, L., 2008. Trademark sales, entry, and the value of reputation. Int. Econ. Rev. 49 (2), 547–576.

McCrary, J., 2008. Manipulation of the running variable in the regression discontinuity design: a density test. J. Econ. 142 (2), 698–714.

Melnik, M.I., Alm, J., 2002. Does a seller's ecommerce reputation matter? Evidence from eBay auctions. J. Ind. Econ. 50 (3), 337–349.

Nieto-Garcia, M., Resce, G., Ishizaka, A., Occhiocupo, N., Viglia, G., 2019. The dimensions of hotel customer ratings that boost RevPAR. Int. J. Hosp. Manag. 77, 583–592.

O'Connor, K., Cheema, A., 2018. Do evaluations rise with experience? Psychol. Sci. 29 (5), 779–790.

Phillips, P., Zigan, K., Silva, M.M.S., Schegg, R., 2015. The interactive effects of online reviews on the determinants of Swiss hotel performance: a neural network analysis. Tour. Manag. 50, 130–141.

Piramuthu, S., Kapoor, G., Zhou, W., Mauw, S., 2012. Input online review data and related bias in recommender systems. Decis. Support Syst. 53 (3), 418–424.

Proserpio, D., Zervas, G., 2017. Online reputation management: estimating the impact of management responses on consumer reviews. Mark. Sci. 36 (5), 645–665.

Resnick, P., Zeckhauser, R., Swanson, J., Lockwood, K., 2006. The value of reputation on eBay: a controlled experiment. Exp. Econ. 9 (2), 79–101.

Roos, G., Pike, S., Fernstrom, L., 2005. Managing Intellectual Capital in Practice. Butterworth-Heinemann,, Oxford.

Shapiro, C., 1982. Consumer information, product quality, and seller reputation. Bell J. Econ. 13 (1), 20–35.

Shapiro, C., 1983. Premiums for high quality products as returns to reputations. Q. J. Econ. 98 (4), 659–680.

Sikora, R.T., Chauhan, K., 2012. Estimating sequential bias in online reviews: a Kalman filtering approach. Knowl. -Based Syst. 27, 314–321.

Statista, 2018. TripAdvisor. ⟨https://www.statista.com/study/42474/tripadvisor/⟩. (Accessed 5 June 2018).

Tadelis, S., 1999. What's in a name? Reputation as a tradable asset. Am. Econ. Rev. 89 (3), 548–563.

Tadelis, S., 2002. The market for reputations as an incentive mechanism. J. Political Econ. 110 (4), 854–882.

Tadelis, S., 2003. Firm reputation with hidden information. Econ. Theory 21 (2), 635–651.

Torres, E.N., Singh, D., Robertson-Ring, A., 2015. Consumer reviews and the creation of booking transaction value: lessons from the hotel industry. Int. J. Hosp. Manag. 50, 77–83.

TripAdvisor, 2018. TripAdvisor Path to Purchase. ⟨https://www.tripadvisor.com/TripAdvisorInsights/w2324⟩. (Accessed 29 December 2018).

Tuominen, P., 2011. The influence of TripAdvisor consumer-generated travel reviews on hotel performance. In: Proceedings of the Nineteenth Annual Frontiers in Service Conference, University of Hertfordshire Business School Working Paper.

Viglia, G., Minazzi, R., Buhalis, D., 2016. The influence of E-word-of-mouth on hotel occupancy rate. Int. J. Contemp. Hosp. Manag. 28 (9), 2035–2051.

Xie, K.L., Zhang, Z., Zhang, Z., 2014. The business value of online consumer reviews and management response to hotel performance. Int. J. Hosp. Manag. 43, 1–12.

Yang, J., Mai, E., 2010. Experiential goods with network externalities effects: an empirical study of online rating system. J. Bus. Res. 63 (9–10), 1050–1057.

Yang, Y., Park, S., Hu, X., 2018. Electronic word of mouth and hotel performance: a meta-analysis. Tour. Manag. 67, 248–260.

Ye, Q., Law, R., Gu, B., 2009. The impact of online user reviews on hotel room sales. Int. J. Hosp. Manag. 28 (1), 180–182.

Ye, Q., Law, R., Gu, B., Chen, W., 2011. The influence of user-generated content on traveler behavior: an empirical investigation on the effects of E-word-of-mouth to hotel online bookings. Comput. Hum. Behav. 27 (2), 634–639.

Zervas, G., Proserpio, D., Byers, J.W., 2021. A first look at online reputation on Airbnb, where every stay is above average. Mark. Lett. 32 (1), 1–16.

Zhang, J.Q., Craciun, G., Shin, D., 2010. When does electronic word-of-mouth matter? A study of consumer product reviews. J. Bus. Res. 63 (12), 1336–1341.

Zhu, F., Zhang, X., 2010. Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. J. Mark. 74 (2), 133–148.