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Online social media play an important role in today's consumer markets. Surveys find that consumers spend an average of 22% of online time on social media sites *(Nielsen Wire, 2010)*, and their purchase decisions are heavily influenced as a result. Given its growing influence, businesses increasingly take an active role in online social media *(Kaplan, Haenlein, 2010)*.

For many businesses, their first step in online social media takes the form of management responses. Management responses refer to a business's effort to interact with and respond to customer comments on experiences with the business or its products and services. Management response is especially valuable for businesses in the service industry, as consistency in service quality is difficult to achieve and service failure is often inevitable. Traditionally, customer complaints on service failure are addressed in private between the complaining customers and the management in a process called service recovery. The objective of service recovery is to identify the source of complaints, restore customer satisfaction, and prevent customer exits *(Maxham, 2001; Smith et al., 1999; Goodwin, Ross, 1992)*. The growing popularity of online social media, however, presents new challenges to service providers. Customers increasingly express their dissatisfaction by posting negative comments in online social media without interacting with the management. To provide service recovery to these customers, service providers must respond publicly to these comments in online social media. The public nature of the online recovery effort, however, requires the service providers to consider not only how their responses influence the complaining customers but also how they influence customers who observe the complaints and the management responses *(Harrison-Walker, 2001)*.

The goal of this study is thus twofold. First, we analyze the impact of online management responses on customers who receive the responses. We consider how the impact varies with customers' satisfaction level. The key challenge in the analysis is to control for possible regression toward the mean in customer satisfaction and for heterogeneity in customer preference for hotels. We develop a panel data regression model that controls for both effects. Second, we assess the influence of online management responses not only on customers who received the responses but also on customers who observed the responses. We extend fairness theory and propose that observing management responses to others but not receiving themselves could have a negative impact on customers who complained about the service.

Using panel data of online customer reviews and online management responses at a major Chinese travel agent, we have two main findings. First, we find that online management responses are highly effective on customers who are very unsatisfied with the service provider (i.e., those give a rating of 1 or 2) but have limited influence on other customers. Second, our result reveals that online management responses also influence customers who observe but did not receive management responses. In particular, we find that online management responses reduce future satisfaction of complaining customers who observe management response to others but do not receive responses themselves. We show the result can be explained by a new type of fairness concern — peerinduced fairness *(Ho, Su, 2009)* — due to the public nature of online management responses.

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Online Social Media and Word of Mouth (WOM)

Online social media have become an important source of product information. Consumers participate in social media in a variety of ways, ranging from reading blogs, to seeking information from friends on social networks, to visiting consumer review forums. Among the growing diversity in online social media, consumer review forums remain the most important social media source for product information, as over 60% of consumers read customer reviews online prior to making purchases *(Lightspeed Research, 2011)*.

The importance of online social media, particularly online customer review forums, has attracted significant attention in recent studies *(Chen et al., 2007; Chevalier, Mayzlin, 2006; Clemons et al., 2006; Dellarocas, 2003; Duan et al., 2009; Li, Hitt, 2008)*. Existing studies consistently show that consumer reviews have significant impacts on consumer purchase decisions *(Chevalier, Mayzlin, 2006; Duan et al., 2008; Forman et al., 2008; Hu et al., 2008; Zhu, Zhang, 2010)*, and they have increasingly been viewed as a new element in the marketing communications mix *(Chen, Xie, 2008; Chen et al., 2004; Dellarocus et al., 2007)*.

Online social media, however, is a double-edged sword for businesses. Although positive customer comments can increase sales, negative comments are often more influential than positive ones *(Chevalier, Mayzlin, 2006)*, and customers with strong negative views are more motivated to post in online social media than customers with average views *(Hu et al., 2008)*. Although extensive academic research has examined the influence of consumer reviews and their implications for marketing and product diversification strategies *(Chen, Xie, 2008; Clemons et al., 2006)*, little research has been done to understand how management should respond to customer reviews in online social media. In this study, we recognize that managing and responding to customer comments has become an important element of a firm’s online social media strategy. We develop an empirical model to inform the management of the effectiveness of such strategies.

Customer Satisfaction and Service Recovery

In service organizations, mistakes and service failures are impossible to eliminate *(Kim et al., 2009; Susskind, 2002)*. Studies have shown that failures themselves do not necessarily lead to customer dissatisfaction, since most customers accept that things may sometimes go wrong *(Del R´ıo-Lanza et al., 2009)*. Instead, the service provider’s response to the failure or lack of response is the most likely cause of dissatisfaction *(Hoffman et al., 1995; Smith et al., 1999)*. Hart et al. *(1990)* found that more than half of all management efforts to respond to customer complaints actually reinforce negative reactions to a service failure. Conversely, McCollough and Bharadwaj *(1992)* discovered that customers receiving service recovery after a service failure could perceive satisfaction as high as or even higher than those who did not encounter such service failure, a phenomenon they called service recovery paradox. In general, these studies suggest that service recovery could have a significant impact on customer satisfaction. However, there are significant variations in its impact *(Hart et al., 1990; McCollough et al., 2000; Smith et al., 1999)*.

Online Management Responses. In online social media, service recovery typically takes the form of management responses. The objective of the management is to provide economic or social resources to compensate customers for losses incurred due to service failures *(Smith et al., 1999)*. Service providers can offer a variety of resources in their response to customer complaints, ranging from financial compensation such as a discount for future services to social resources such as an apology. These efforts influence customer satisfaction by moderating customer perception of justice and fairness *(Mccoll-Kennedy, Sparks, 2003)*. For example, Tax et al. *(1998)* find that compensation is an important element in the recovery effort to remedy distributive justice. Similarly, Smith et al. *(1999)* and Walster et al. *(1973)* indicate that social resources such as an apology help remedy interactional justice perceived by customers. We thus propose the following:

Hypothesis 1a: Customers' satisfaction with a service provider increases after receiving online management responses from the service provider.

The impact of online management responses on customer satisfaction varies with the severity of service failure and the degree of injustice or inequity perceived by customers. Social exchange theory has long recognized that justice and fairness are one of the key drivers in social interactions *(Oliver, Swan, 1989)*. Behavioral economics studies also reveal that fairness concern plays an important role in individual decision makings *(Bolton, Ockenfels, 2000)*. In the context of online management responses, customers assess the level of injustices in the service failures and form an expectation with regard to the likelihood of receiving management responses *(Mccoll-Kennedy, Sparks, 2003; Miller et al., 2000)*. Customers who perceive grave injustice or inequity have a higher expectation of receiving management responses. As such, online management responses will be most effective on these customers. We thus propose the following:

Hypothesis 1b: Online management responses have a more positive impact on low satisfaction customers.

Peer-Induced Fairness. Although prior service recovery literature focuses on justice and equity between customers and service providers, the public nature of online management responses introduces a new type of justice and fairness concerns — peer-induced fairness. Peer-induced fairness refers to the phenomenon that individuals often look to their peers as a reference *(Ho, Su, 2009)*. Their satisfaction decreases when individuals perceive themselves being treated worse than their peers *(Del R´ıo-Lanza et al., 2009)*. In the context of online management responses, customer satisfaction is determined not only by whether they receive responses from the service provider but also by the comparison to the responses received by other customers. Observing online management responses to others but not receiving responses oneself creates peer-induced injustice and decreases a customer's satisfaction.

Hypothesis 2a: Observing others receiving online management responses without receiving responses themselves decreases customers' satisfaction with the service provider.

The peer-induced injustice varies with the severity of service failure. A customer who is satisfied with a service provider does not expect to receive online management responses in the first place and will not perceive peer-induced injustice when others receive responses from the management. On the other hand, customers who are dissatisfied with the service provider are most likely to feel insulted when they observe others receiving management responses but do not receive responses themselves. We thus propose the following:

Hypothesis 2b: Observing others receiving online management responses without receiving responses themselves has a more negative impact on low satisfaction customers.

DATA AND EMPIRICAL METHODOLOGY

Data

The data in this study were retrieved from Ctrip.com (NASDAQ: CTRP), the largest online travel agency in Mainland China. Ctrip.com provides an online forum for customers to review their hotel experiences and the hotel management to respond to customer reviews.[2]

To ensure the quality and authenticity of online customer reviews, Ctrip.com allows only customers who booked through Ctrip to post one review for each stay within a week after the stay. To encourage customer reviews, Ctrip emails customers a reminder after each stay, and those who submit reviews are eligible to win substantial prizes from the company. The promotion motivates a large number of their customers to post reviews online. Although Ctrip does not disclose the percentage of customers who submitted reviews online, our data indicate that its customer reviews are, overall, representative of the underlying customer population. In particular, the distribution of review ratings in our data (Figure 1) resembles a normal

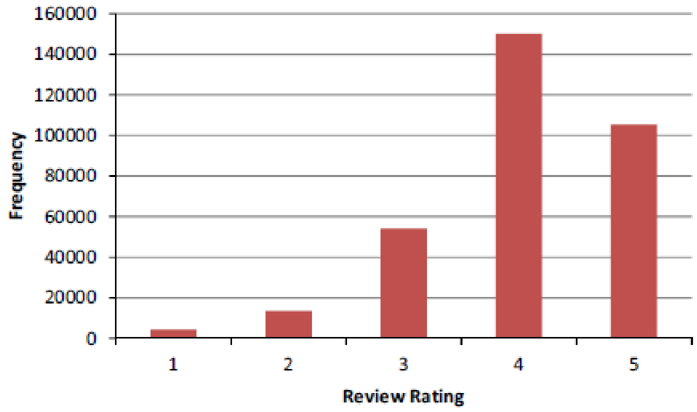
[2] Ctrip.com is one of the first online travel agencies that allows hotel management to respond to customer comments. Today, most online travel agencies and social media sites such as Expedia, Tripadvisor, and Yelp provide management response capabilities.

distribution instead of a bimodal J-shaped distribution observed in prior studies on customer reviews *(Hu et al., 2009)*.

Figure 1.

Distribution of Customer Review Ratings

Review Rating (rounded to the nearest integer)	Frequency	Percent	Cumulative Percent
1	4313	1.36	1.36
2	13399	4.23	5.60
3	52566	16.60	22.20
4	144849	45.76	67.96
5	101551	32.08	100.00
Total	316568	100.0	



We developed a crawler to automatically download web pages of reviews and information of hotels from Ctrip.com and developed another system to parse HTML and XML web pages into our database. We used the crawler to retrieve all available hotel and customer review information from Ctrip.com from the website inception to October 2009. For each hotel in our data set, we collected customer review information for each posting, including author, review date, review ratings (from 1 to 5), review content, the presence of management response to the review, and the publication date of the management response. Table 1 provides a summary description of the data.

Table 1 Summary Statistics

Variables	Value	Percentage
Number of cities	49	N/A
Number of hotels	5831	N/A
Number of hotels without star ratings	3981	68.27%
Number of 2-star hotels	86	1.47%
Number of 3-star hotels	702	12.04%
Number of 4-star hotels	720	12.35%
Number of 5-star hotels	342	5.87%
Number of hotels with reviews	5831	100.00%
Number of hotels with management responses	2916	50.00%
Number of customer reviews	316,568	N/A
Number of reviews with management response	73,973	22.50%
Number of unique reviewers	165,221	N/A
Average number of hotels stayed per reviewer	1.79	N/A

The table 1 shows that Ctrip.com has a total of 5831 hotels across 48 cities in China. All hotels have received at least one online customer review, and half of the hotels have provided management responses to online reviews. The high percentage of Chinese hotels with management responses indicates that online management responses have been increasingly used by Chinese service providers as a tool to provide service recovery in online social media. The table also shows a significant number of customer reviews on Ctrip.com. In total, Ctrip.com hosts 316,568 customer reviews, equivalent to 54 reviews per hotel.

Table 2 presents the distribution of online management responses to customer reviews and percentage of customers who later post reviews on the same hotels and the distribution of their subsequent review ratings. A surprising finding of Table 2 is that hotels provide about the same level of management responses regardless of review ratings. On average, 23% of customer reviews receive online management responses. Those reviews with the lowest rating (1 of 5) have a slightly higher chance to receive online management responses (25%) while other customers have a 22%–23% probability to receive online management responses. Table 2 also reveals that 7% of customers review the same hotel a second time. The repeat reviewing probability varies with review ratings. Customers who gave good review ratings have a 7%–8% probability of reviewing the same hotel again while customers who gave poor review ratings have a 3% probability of reviewing the same hotel again.

Table 3 provides the definitions of the independent variables and their summary statistics. The table shows that the average customer review rating is 4.08 and 2% of the reviews have a rating of 1 or 2. Twenty-five percent of the customers that provided reviews received responses from the management and 40% of these customers observed management responses to others before their postings of the reviews.

Table 2 Subsequent Review Rating Distribution

Review rating	Number of reviews	Percentage with service recovery	Percentage with a subsequent review of the same hotel	Distribution of subsequent review rating				
				1	2	3	4	5
1	4313	25%	3%	38%	19%	21%	17%	5%
2	13,399	23%	3%	6%	29%	41%	20%	4%
3	52,566	22%	6%	1%	6%	50%	40%	4%
4	144,849	23%	8%	0%	1%	12%	71%	16%
5	101,551	23%	8%	0%	0%	2%	26%	72%
Total	316,568	23%	7%	1%	2%	14%	50%	34%

Table 3 Variable Descriptions

Variable name	Description	Mean	SD
$Rating_{ijt}$	Rating from 1 to 5, given by consumer i to indicate his/her satisfaction with hotel j at time t.	4.08	0.73
$ReceivedResponse_{ijt-1}$	Dummy variable, to indicate whether customer i has received online management response from hotel j for his/her prior online word of mouth posting. It takes the value of 1 if the management responded to his/her prior posting. Otherwise, it takes the value of 0.	0.25	0.43
$ObservedResponse_{ijt-1}$	Dummy variable, to identify whether customer i observed online management response from hotel j to other customers within the 20 most recent reviews at time t.	0.40	0.49
$LowSatisfaction_{ijt-1}$	Dummy variable, to indicate that customer i has given the lowest rating for his/her previous experience with hotel j. It takes the value of 1 when $Rating_{ijt-1}$ is 1 or 2; otherwise it takes the value of 0.	0.02	0.07

Empirical Approach

Regression toward the Mean and the Impact of Online Management Responses. To quantify the impact of online management responses on customer satisfaction, we use a panel data approach on customers who provide multiple reviews of the same hotel. This identification strategy allows us to control for heterogeneity in individual preferences for hotels and identify the impact of online management responses by comparing changes in customer review ratings of those who receive management responses with those who do not receive responses. One of the challenges in this identification strategy that that customer review ratings may improve without management responses. This is due to the effect of regression toward the mean *(Stigler, 1997)*. From a statistics perspective, regression toward the mean is the phenomenon that if one measure of a random variable is extreme, the next measure of the random variable is likely to be less extreme and closer to its mean *(Barnett et al., 2005; Galton, 1886; Stigler, 1997).*[3] The phenomenon can bias the estimation of treatment effect in situations where treatments are applied to individuals with extreme measures because regression toward the mean is co-mingled with the influence of treatments.[4]

To control for the influence of regression toward the mean, a common strategy is to leverage the fact that the treatment (i.e., management responses) is not applied to all individuals with extreme measures, while all such customers are influenced by regression toward the mean. In addition, the degree of regression toward the mean varies with the extremeness of the prior measure. The combination suggests that regression toward the mean can be controlled by including the treatment variable and the difference between the prior measure and the mean *(Barnett et al., 2005; George et al., 1997).*

One challenge in the above approach is that the mean satisfaction of a given customer toward a given hotel is not observable to researchers. Customers are often heterogeneous in their preferences for hotels. For example, one customer may enjoy the contemporary design of W hotels, while another customer may find such design a turnoff. Modeling customer heterogeneous preference for hotels requires more than the inclusion of customer fixed effects or hotel fixed effects, as the heterogeneity arises in the interaction between hotels and customers. To allow customers to have different preferences for hotels, we thus model the mean ratings using fixed effects for each hotel–customer pair as follows:

$$\begin{aligned} Rating_{ijt} &= \theta_{ij} + \rho(Rating_{ijt-1} - \theta_{ij}) \\ &\quad + \beta_1 ReceivedResponse_{ijt-1} + \epsilon_{ijt}. \qquad (1) \end{aligned}$$

The fixed effect O_{ij} in the above equation identifies the mean rating of customer i on hotel j. The differences between ($Rating_{ijt-1}$ — O_{ij}) identify the degree to which customer i’s rating on hotel j for a given stay deviates from the mean rating. The coefficient quantifies the effect of regression toward the mean. $ReceivedResponse_{ijt-1}$ is the treatment variable that takes the value of 1 if the management of hotel j responded to customer i’s previous review of the hotel before time t. Otherwise, it takes the value of 0. Ctrip.com automatically informs the reviewer through email if his or her review receives a response from the management. So, the variable is an accurate measure of whether a reviewer is aware of the response from the management. The coefficient B_1 thus captures the effect of online management responses on customer review rating as indicated in H1a.

It is useful to note that Equation (1) is equivalent to the following equation with newly defined fixed effects O'_{ij}:

$$\begin{aligned} Rating_{ijt} &= \theta'_{ij} + \rho Rating_{ijt-1} \\ &\quad + \beta_1 ReceivedResponse_{ijt-1} + \epsilon_{ijt}, \qquad (2) \end{aligned}$$

where O'_{ij} = (1 — p) O_{ij}.

The above equation suggests that the inclusion of the prior customer review rating controls for the effect of regression toward the mean, while the inclusion of the treatment variable identifies the effect of online management responses. We further recognize that regression toward the mean may not necessarily be a linear function of prior review rating. We thus treat prior review rating as a category variable using a vector representation.

$$\begin{aligned} Rating_{ijt} &= \theta'_{ij} + \boldsymbol{\rho}\mathbf{Rating}_{ijt-1} \\ &\quad + \beta_1 ReceivedResponse_{ijt-1} + \epsilon_{ijt}. \qquad (3) \end{aligned}$$

[3] For example, a student’s grade is influenced by both his capability and luck. A student who scored low on one test could just have a bad luck and is likely to score higher in the next test without any intervention.

[4] In the example in footnote 3, schools that provide tutoring to students with low scores may mistakenly attribute all the increase in student grades to the influence of tutoring although part of the increase is likely to be caused by regression toward the mean.

In the above equation, Rating_{ijt-1} is a vector of dummy variables that captures customer's prior review rating and *p* is a vector of coefficients identifying the effect of regression toward the mean for customers with different prior review ratings.

H1b suggests that the influence of online management responses is stronger for low satisfaction customers. To test the hypothesis, we create a new dummy variable $LowSatisfaction_{ijt-1}$ to represent a customer who has indicated a low level of satisfaction in his or her previous review of the hotel:

$$LowSatisfaction_{ijt-1} = \begin{cases} 1, & \text{if } Rating_{ijt-1} \leq 2 \\ 0, & \text{otherwise} \end{cases}. \quad (4)$$

We then incorporate the interaction between the treatment variable and the low satisfaction dummy variable to assess whether online management response is more influential on low satisfaction customers.

$$\begin{aligned} Rating_{ijt} = \theta'_{ij} &+ \boldsymbol{\rho}\mathbf{Rating}_{ijt-1} \\ &+ \beta_1 ReceivedResponse_{ijt-1} \\ &+ \beta_2 ReceivedResponse_{ijt-1} \\ &\times Lowsatisfaction_{ijt-1} + \epsilon_{ijt}. \end{aligned} \quad (5)$$

Impact on Customers Who Observe Management Responses. We next assess the influence of online management responses on customers who observed management responses to others but did not receive responses themselves. To perform the analysis, we introduce a new dummy variable $ObservedResponse_{ijt-1}$ to assess whether customer i had posted reviews on hotel j before time t and whether the hotel had provided management responses to others in the 20 most recent reviews by time t. We choose 20 most recent reviews because each customer review page on Ctrip shows 20 reviews in reverse chronological orders. Prior studies suggest that customers rarely go beyond the first page in online information search *(Smith, Bryjolfsson, 2001)*. Therefore, customers most likely form their view on the hotel's management responses based on what they observe on the first page. It is useful to note that, unlike the variable on receiving management responses, we do not know with certainty that customers actually observe management responses to others. However, given our empirical design of leveraging customers with repeated reviews of the same hotel, the likelihood of these customers actually observing the management responses (if available) is very high. This is because, to post customer reviews, these customers must first go to the customer review page of the hotel. Man- agement responses are clearly visible and highlighted on that page. Therefore, these customers are most certainly aware of the presence of management responses. In addition, in case some customers do not actually observe management responses, the coefficient on the dummy variable $ObservedResponse_{ijt-1}$ is likely to be biased downwards. Thus, it will bias against finding a significant impact of management responses. H2a suggests that the influence of observing online management responses to other customers is negative due to peer-indicated fairness concerns and the influence varies with customer prior satisfaction with the hotel. We thus add the dummy variable for observing management responses to others to Equation (5).

$$\begin{aligned} Rating_{ijt} = \theta'_{ij} &+ \boldsymbol{\rho}\mathbf{Rating}_{ijt-1} \\ &+ \beta_1 ReceivedResponse_{ijt-1} \\ &+ \beta_2 ReceivedResponse_{ijt-1} \\ &\times Lowsatisfaction_{ijt-1} \\ &+ \beta_3 ObservedResponse_{ijt-1} + \epsilon_{ijt}. \end{aligned} \quad (6)$$

Finally, H2b suggests that the negative influence of online management responses on customers who observe but do not receive management responses is higher for low satisfaction customers. To test the hypothesis, we add the interaction term between observing responses to others and the dummy variable for low satisfaction to Equation (6). H2b indicates that the coefficient on the interaction term should be negative.

$$\begin{aligned} Rating_{ijt} = {} & \theta'_{ij} + \boldsymbol{\rho}\mathbf{Rating}_{ijt-1} \\ & + \beta_1 ReceivedResponse_{ijt-1} \\ & + \beta_2 ReceivedResponse_{ijt-1} \\ & \times Lowsatisfaction_{ijt-1} \\ & + \beta_3 ObservedResponse_{ijt-1} \\ & + \beta_4 ObservedResponse_{ijt} \\ & \times LowSatisfaction_{ijt-1} + \epsilon_{ijt}. \end{aligned} \tag{7}$$

Self-Selection in Repeated Ratings. Another issue in analyzing the relationship between management responses and customer satisfaction is that our observations are not random. Our empirical approach relies on observing review ratings of customers who provide multiple reviews of the same hotel. Table 2 shows that the probability of customers providing a subsequent review of the same hotel varies with their satisfaction with the prior stay. This leads to a potential self-selection bias in our data. To control for the problem, we use Heckman's *(1979)* two-step approach to correct the self-selection bias. Specifically, in the first step, we explicitly model the probability of a customer posting a second review on the same hotel using a Probit model based on his prior review rating. We also include the hotel dummy variables in the model to control for heterogeneity across hotels in attracting returning customers.

$$HasReview^*_{ijt} = \beta_1 ReviewRating_{ijt-1} + \eta_j + \epsilon_{ijt},$$

$$P(HasReview^*_{ijt} = 1) = \Phi(HasReview^*_{ijt} \geq 0). \tag{8}$$

In the second step, we use the predicted value from the Probit model to calculate the invert Mills ratio for each customer review and include the ratio in the regression models to control for the self-selection bias.

DATA ANALYSIS

Results

Table 4 presents the results of the analysis. We take a step-wise approach and start with the analysis on how a customer's receipt of online management responses influences his subsequent rating of the hotel. Column 1 reports the average influence of online management responses with control for regression toward the mean and customer heterogeneity in their preference for hotels. The analysis suggests a significant regression toward the mean effect for customers who report a prior review rating of 1. For these customers, their average subsequent rating increases by 0.376 (on a 1–5 scale) without any interventions from the service provider. This result suggests that many 1-star ratings are due to random events in service encounters that are unlikely to repeat in the future. Interestingly, there is little regression toward the mean effect for customers who give higher review ratings, indicating that these ratings are more reflective of the underlying service quality of the service provider.

Table 4 Analysis of Online Service Recovery on Customer Satisfaction (*LowSatisfaction* = {1, 2})

	Coefficients (SE)			
Variables	Equation (3)	Equation (5)	Equation (6)	Equation (7)
$ReceivedRecovery_{ijt-1}$	0.020 (0.022)	0.009 (0.022)	0.005 (0.022)	0.003 (0.022)
$ReceivedRecovery_{ijt-1}$* $LowSatisfaction_{ijt-1}$		0.429 (0.095)***	0.428 (0.095)***	0.581 (0.121)***
$ObservedRecovery_{ijt-1}$			0.022 (0.018)	0.026 (0.018)
$ObservedRecovery_{ijt-1}$* $LowSatisfaction_{ijt-1}$				−0.214 (0.103)**
Previous rating = 1.0	0.376 (0.124)***	0.294 (0.125)**	0.296 (0.125)**	0.336 (0.126)***
Previous rating = 2.0	0.049 (0.076)	−0.041 (0.079)	−0.041 (0.079)	0.003 (0.081)
Previous rating = 3.0	0.004 (0.043)	0.002 (0.043)	0.001 (0.043)	0.001 (0.043)
Previous rating = 4.0	−0.023 (0.023)	−0.023 (0.023)	−0.024 (0.023)	−0.024 (0.023)
Previous rating = 5.0 (Baseline)	–	–	–	–
Self-selection adjustment	1.360 (0.218)***	1.365 (0.218)***	1.364 (0.218)***	1.367 (0.218)***
Autocorrelation	−0.018 (0.012)	−0.016 (0.012)	−0.016 (0.012)	−0.017 (0.012)
R-square	91.38%	91.41%	91.41%	91.42%
Number of observations	22,208	22,208	22,208	22,208

***$p < 0.001$; **$p < 0.01$. Fixed effect for all combinations of (customer × hotel) is included but not reported.

We next consider the influence of online management responses. Our analysis in column 1 reveals that online management responses have no significant mean impact on future satisfaction of customers who received responses. The insignificance, however, masks significant variations in the influence of online management responses. In column 2, we allow the influence of online management responses to be different for low satisfaction customers who give a prior review rating of 1 or 2. The results show that receiving responses from a service provider increases the satisfaction of low satisfaction customers by 0.429 (on a 1–5 scale). The result is statistically significant and supports H1b. The analysis also shows that the coefficient on the self-selection adjustment is significant, indicating the presence of self-selection bias in our data and the importance of making adjustment for the bias.

We next consider the impact of online management responses on customers who observe management responses to others but do not receive responses themselves. Columns 3 and 4 of the table report the results. Column 3 shows that the mean effect of observing online management responses to others but not receiving themselves is insignificant, rejecting H2a. However, column 4 shows that observing but not receiving management responses has a significant and negative impact on customers who are unsatisfied about their previous encounter with the service provider. For these customers, observing online management responses to others without receiving one reduces their satisfaction by 0.214 on a 1–5 scale. This result supports H2b.

Overall, our results suggest that the influence of online management responses varies greatly across customers. Providing management responses can increase the future satisfaction of customers who are unsatisfied with their prior experience, but it has limited influence on the satisfaction of other customers. This result contrasts with the practice reflected in Table 2 that hotels provide online management responses almost randomly without regard to customer review ratings. Moreover, we find that online management responses negatively affect low satisfaction customers when they observe others receiving management responses but do not receive responses themselves. The finding supports the peer-induced fairness theory and indicates that concerns for peers receiving better treatment from the service provider negatively influence a customer’s future review ratings. Collectively, our results suggest that low satisfaction customers should be granted priority in receiving management responses.

Questions for your consideration

1. What is the main research question of the article?
2. What are the drawbacks of the research design (data, methods, analysis)?
3. What managerial implications of the findings do you suggest?
4. What new research methods can you suggest that were not available for the original research project? Is this research still relevant?
5. For what areas these research ideas may also be applicable? Illustrate with an example highlighting how the research design should be adapted.