The Impact of Online Service Recovery on Customer Satisfaction: Empirical Evidences from Service Operations

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The Impact of Online Service Recovery on Customer Satisfaction: Empirical Evidences from Service Operations

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ABSTRACT
Online service recovery tools such as managerial responses are increasingly used by service providers to address customer concerns in online WOM platforms. In this paper, we analyze the effectiveness of such online service recovery effort on customer satisfaction using data retrieved from a major online travel agency in China. We find that online service recovery is highly effective among the least satisfied customers but has limited influence on other customers. Moreover, we show that the public nature of online service recovery introduces a new dynamic among customers. While online service recovery increases future satisfaction of the complaining customers who receive the recovery effort, it significantly decreases future satisfaction of those complaining customers who observe but do not receive the recovery effort. We show the result is consistent with the peer-induced fairness theory. In addition, this study reveals that a customer’s satisfaction with a service provider demonstrates mean reversion over multiple interactions. It is important to control for such dependence in assessing the true impact of online service recovery.

Keywords
Online Managerial Response; Service Recovery; Customer Satisfaction; Peer-Induced Fairness; Expectations-confirmation Theory; Service Operations

INTRODUCTION
Customer satisfaction has been widely noted as one of the most important elements in service operations (Davis and Maggard, 1990; Heikkilä, 2002). It drives customer loyalty and ultimately determines firm profitability and growth (Heskett et al. 1994). However, service failure is often inevitable. Effective service recovery plays a critical role for the management to maintain customer satisfaction and loyalty (Miller et al, 2000).

Traditionally, service recovery is made in private between complaining customers and the management. The goal of the management is to address customer complaints, restore customer satisfaction and prevent customer exits (Maxham 2001, Smith et al. 1999, Goodwin and Ross 1992). The growing popularity of online WOM platforms, however, presents new challenges for service recovery operations. Customers increasingly express their dissatisfaction by posting negative comments on infomediaries (e.g. tripadvisor.com) or other intermediaries (e.g. expedia.com). These negative comments differ from traditional customer complaints in an important way: they are “permanently” archived and freely available to future audience (Dellarocas 2003). To address these negative comments, Chinese service operators increasingly use online service recovery tools such as managerial responses to interact with customers. The public nature of the online recovery effort, however, requires the service operators to consider not only how its service recovery effort influences the complaining customers but also how it influences customers who observe the complaints and recovery efforts (Harrison-Walker 2001). At the same time, the growing popularity of online WOM platforms also presents opportunities to service providers. In particular, customer comments online enable service providers to collect and analyze how customer satisfaction evolves over time. The longitudinal nature of online customer review data allows service providers to understand the dynamics of customer satisfactions and the effect of service recovery effort on the dynamics, which are difficult to assess using the traditional survey approach.

The goal of this study is thus two-folded. First, we analyze the dynamics of customer satisfaction over time and the influence of online service recovery on the dynamics. Different from the extant service recovery literature, our focus is on how...
individual customers’ satisfaction with a service provider changes over multiple interactions and how online service recovery influences the dynamics. We extend expectations-confirmation theory and propose that customer reviews are not independent over time because a customer’s previous satisfaction with a service provider influences her future expectations. Second, we assess the influence of online service recovery not only on customers who received the recovery effort but also on customers who observed the recovery effort. We extend fairness theory and propose that observing recovery effort for others could have a significant impact on customer satisfaction.

Using a panel data of WOM and online service recovery effort in the form of online managerial responses at a major Chinese travel agent, we confirm both propositions. Our result reveals that customer satisfaction with a service provider demonstrates mean reversion, i.e. customers with unsatisfactory experience are more likely to express satisfaction in the next interaction while customers with prior satisfactory experience are more likely to express dissatisfaction in the next interaction. The result supports the expectations confirmation theory. We also show that the impact of online service recovery varies with customer satisfaction level. It is the most effective on customers with the lowest satisfaction but has limited influence on other customers. Our result further reveals that online recovery effort not only has a significant impact on the complaining customers, but also has a significant impact on customers who observe the recovery effort. In particular, we find that service recovery effect negatively influences customers who had dissatisfactory experience but did not receive online recovery effort. We show the result can be explained by a new type of fairness concern because of the public nature of service recovery effort - peer-induced fairness (Ho and Su 2009).

The rest of the paper is organized as follows. In Section 2, we provide the background and the theoretical foundation. Section 3 describes the data and the empirical methodology. The results are presented in Section 4. We conclude in Section 5.

BACKGROUND AND THEORY

Online WOM

With the development of Internet technology and electronic commerce, online customer reviews are increasingly becoming important sources of product information (Chevalier and Mayzlin 2006). According to a survey by Shop.org (2007), more than half of online buyers read customer reviews prior to making purchases. The importance of online word-of-mouth has attracted significant attention in recent studies (Chen et al. 2007; Chevalier and Mayzlin, 2006; Clemons et al. 2008; Dellarocas 2003; Duan et al. 2009; Li and Hitt 2009). Existing studies consistently show that online WOM have significant impacts on product or service sales (Chevalier and Mayzlin 2006, Duan et al. 2008) and it has increasingly been viewed as a new element in the marketing communications mix (Chen and Xie, 2008).

Online WOM, however, is a double-edged sword for businesses. While positive reviews can increase sales, negative reviews are much more influential than positive reviews (Chevalier and Mayzlin, 2006) and consumers with strong negative views are more motivated to post online reviews than consumers with average views (Hu et al. 2007). Although extensive academic research has examined the influence of online WOM and its implications for marketing and product diversification strategies (Chen and Xie 2008; Clemons et al. 2008), little research has examined how to manage negative WOM and the effectiveness of such strategies. In this study, we recognize that managing negative WOM has increasingly become an important element of service management. We extend theories on service recovery and inform service managers of the strategies and their effectiveness in managing online WOMs.

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 consumers accept that things may sometimes go wrong, especially in services operations (del Río-Lanza et al. 2009). Instead, the service provider’s response to the failure or lack of response is the most likely cause of dissatisfaction. Service recovery activities may either reinforce customer relationships or compound the failure (Hoffman et al., 1995; Smith et al., 1998). Hart et al. (1990) found that more than half of all efforts to respond to customer complaints actually reinforce negative reactions to a service. 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 recovery effort could have a significant impact on customer satisfaction. However, there are significant variations in its impact (McCollough et al. 2000; Smith et al. 1999; Hart et al. 1990).
**Expectations-confirmation Theory**

To assess how online service recovery affects customer satisfaction, we first need to understand how customer satisfaction is formed. Expectations-confirmation theory, also known as expectation disconfirmation theory, indicates that post-purchase satisfaction is determined by pre-purchase expectations and perceived performance (Anderson and Sullivan 1993; Oliver, 1977, 1980; Spreng et al. 1996, Bhattacharjee 2001; McKinney et al. 2002). The theory suggests that customer satisfaction with a service provider is not solely driven by service performance. It also depends on a customer’s pre-purchase expectation. Performance that meets or exceeds expectation generates satisfaction while experience that does not live up to expectation generates dissatisfaction.

One of the most important factors that drive customer expectation is past product/brand experience (Halstead, 1999; Yi 1990; Spreng et al. 1996; Woodruff et al., 1983). Past experience is especially important for service providers as consumers often have multiple interactions with the same provider and variations in service performance could have significant implications for customer satisfaction. The expectations-confirmation theory suggests that customer satisfaction with multiple interactions is not independent from each other. Instead, customers form expectation based on their previous experience with the service provider. Future service performance that falls short of the previous experience leads to disconfirmation and customer dissatisfaction, while future service performance that exceeds of the previous experience leads to positive confirmation and post-purchase satisfaction. As such, customer satisfaction with a service provider is likely to be negative correlated over time. We thus propose:

**Hypothesis 1:** Customer satisfaction with a service provider demonstrates mean reversion over time. That is, customer subsequent satisfaction is negatively associated with her level of satisfaction in the prior interactions.

**Online Service Recovery and Customer Satisfaction**

Service failures are often unavoidable in service operations. The objective of service recovery 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 for service recovery, ranging from monetary compensation such as discount for future services to social resources such as an apology. These recovery efforts influence customer satisfaction by moderating customer perception of justice and fairness (McColl-Kennedy and Sparks 2003). For example, Tax et al. (1998) find that compensation is the most important element in 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:

**Hypothesis 2a:** A customer’s satisfaction with a service provider increases after receiving online service recovery.

The impact or service recovery 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 is one of the key drivers in social interactions (Oliver and Swan 1989). Behavioral economics studies also reveal that fairness concern plays an important role in individual decision makings (Bolton and Axel Ockenfels 2000). In the context of service recovery, customers assess the level of injustices in the service failure and form expectation with regard to service recovery (Mccoll-Kennedy and Sparks 2003; Miller et al. 2000). Customers who perceive grave injustice or inequity have the highest expectation for service recovery effort from the service provider. As such, the provision of online service recovery will be most effective on these customers. We thus propose:

**Hypothesis 2b:** Online service recovery has the highest positive impact on customer satisfaction for customers who gave the lowest review ratings.

**Online Service Recovery and Peer-induced Fairness**

While prior service recovery literature focuses on justice and equity between customers and service providers, the public nature of online service recovery 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 and Su, 2009). Their satisfaction decreases when individuals perceive lower payoffs or being treated worse than their peers (Río-Lanza, 2009). In the context of online service recovery, customer satisfaction is determined not only by the service recovery effort provided by the service provider but also by the comparison of the service recovery effort to those received by other customers. Observing service recovery to others but not receiving it herself creates peer-induced injustice and decreases customer satisfaction.

**Hypothesis 3a:** Observing others receiving online service recovery without receiving it herself decreases a customer’s 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 service recovery in the first place and will not perceive peer-induced injustice when others receive service recovery effort. On the other hand, customers who are most dissatisfied with the service provider are most likely to feel insulted when they observe others receiving service recovery effort but do not receive it themselves. We thus propose:

**Hypothesis 3b**: Observing others receiving online service recovery without receiving it themselves has the most negative impact on customer satisfaction for customers who give the lowest review ratings.

**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 allows customers to provide online reviews for their hotel stays. It also allows the hotel management to provide managerial response to online customer reviews. Figure 1 provides a sample hotel WOM page from Sofitel Grand Park Hefei with managerial responses to customer complaints.

![Example of Online WOM and Managerial Response on Ctrip.com](image)

**Figure 1: Example of Online WOM and Managerial Response on Ctrip.com**

To ensure the quality of online WOM, Ctrip.com allows only its customers to post reviews and the customers must post within a week after each stay. To encourage submission of online WOM, Ctrip.com emails customers a reminder after each stay and those who submit reviews are eligible to win substantial gifts from the travel agents. The promotion motivates a large number of their customers to post hotel reviews online. While Ctrip.com does not disclose the percentage of customers who submitted online WOM, our data indicates that its customer reviews are, overall, more representative of the underlying customer population. In particular, the distribution of WOM ratings in our data resembles a normal distribution instead of a bimodal J-shaped distribution observed in prior WOM studies (Hu et al. 2009).

We developed a crawler to automatically download web pages of reviews and information of hotels from the travel agent and developed another system to parse HTML and XML web pages into our database. We used the crawler to retrieve all available hotel and WOM 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, date of publishing, review ratings (from 1 to 5), review content, the presence of managerial response to the review, and the publication date of managerial response. Table 1 and 2 provides a summary description of the data. The table 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 managerial responses to online reviews. The high percentage of Chinese hotels with managerial responses indicates that online managerial responses have been increasingly used by Chinese service providers as a tool for service recovery. The table also shows that there are a significant number of customer reviews on Ctrip.com. In total, Ctrip.com hosts 328,777 customer reviews, equivalent to 56 reviews per hotel. About 22% of online customer reviews have received managerial responses.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Value</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Cities</td>
<td>49</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of hotels</td>
<td>5831</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of hotels without star ratings</td>
<td>3981</td>
<td>68.27%</td>
</tr>
<tr>
<td>Number of 2-star hotels</td>
<td>86</td>
<td>1.47%</td>
</tr>
<tr>
<td>Number of 3-star hotels</td>
<td>702</td>
<td>12.04%</td>
</tr>
<tr>
<td>Number of 4-star hotels</td>
<td>720</td>
<td>12.35%</td>
</tr>
<tr>
<td>Number of 5-star hotels</td>
<td>342</td>
<td>5.87%</td>
</tr>
<tr>
<td>Number of hotels with reviews</td>
<td>5831</td>
<td>100.00%</td>
</tr>
<tr>
<td>Number of hotels with managerial response</td>
<td>2916</td>
<td>50.00%</td>
</tr>
<tr>
<td>Number of customer reviews</td>
<td>328777</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of reviews to hotels without star ratings</td>
<td>222795</td>
<td>67.76%</td>
</tr>
<tr>
<td>Number of reviews to 2-star Hotels</td>
<td>3162</td>
<td>0.96%</td>
</tr>
<tr>
<td>Number of reviews to 3-star Hotels</td>
<td>25122</td>
<td>7.64%</td>
</tr>
<tr>
<td>Number of reviews to 4-star Hotels</td>
<td>48041</td>
<td>14.61%</td>
</tr>
<tr>
<td>Number of reviews to 5-star Hotels</td>
<td>29657</td>
<td>9.02%</td>
</tr>
<tr>
<td>Number of reviews with managerial response</td>
<td>73973</td>
<td>22.50%</td>
</tr>
<tr>
<td>Number of authors</td>
<td>165221</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 1 Summary Statistics

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating&lt;sub&gt;ijt&lt;/sub&gt;</td>
<td>Rating from 1 to 5, given by consumer i to indicate his/her satisfaction with hotel j at time t.</td>
<td>3.96</td>
<td>0.83</td>
</tr>
<tr>
<td>ReceivedResponse&lt;sub&gt;ijt-1&lt;/sub&gt;</td>
<td>Dummy variable, to indicate whether customer i has received online managerial response from hotel j for his/her prior online WOM posting. It takes the value of 1 if the management responded to his/her prior posting. Otherwise, it takes the value of 0.</td>
<td>0.02</td>
<td>0.13</td>
</tr>
<tr>
<td>ObservedResponse&lt;sub&gt;ijt&lt;/sub&gt;</td>
<td>Dummy variable, to identify whether customer i observed online managerial response from hotel j to other customers by time t.</td>
<td>0.51</td>
<td>0.50</td>
</tr>
<tr>
<td>LowSatisfaction&lt;sub&gt;ijt-1&lt;/sub&gt;</td>
<td>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&lt;sub&gt;ij,t-1&lt;/sub&gt; is 1, otherwise it takes the value of 0.</td>
<td>0.01</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Table 2 Variable Descriptions

**Empirical Approach**

To identify the effectiveness of online service recovery on customer satisfaction, we keep track of review ratings of the same customer for the same hotel over time and assess how customer satisfaction is influenced by online service recovery effort.
We start with a base model that allows each customer to have her own preference for a given hotel using fixed effects for all possible customer-hotel combinations:

\[ \text{rating}_{ijt} = \theta_{ijt} + \epsilon_{ijt} \quad (1) \]

The fixed effects \( \theta_{ijt} \) not only accommodate customer heterogeneity and hotel heterogeneity, but also accommodate individual idiosyncratic preference for hotels. The noise term \( \epsilon_{ijt} \) captures randomness in service quality experienced by customer \( i \) in hotel \( j \) at time \( t \).

We next incorporate a customer’s previous satisfaction level with a hotel. Hypothesis 1 suggests that consumers’ subsequent satisfaction level with a hotel is influenced by her past experience with the hotel. It is thus necessarily to extend equation (1) to model the dependence between subsequent review ratings and prior review ratings. We use the following equation to capture the dependence:

\[ \text{rating}_{ijt} = \begin{cases} 
\theta_{ijt} + \epsilon_{ijt}, & \text{if } t \text{ is the first time customer } i \text{ interacts with hotel } j \\
\beta_0 + \beta_1 \text{rating}_{ijt-1} + \theta_{ij} + \epsilon_{ijt}, & \text{otherwise} 
\end{cases} \quad (2) \]

The first equation in (2) is the same as equation (1). It suggests that, when a customer first encounters a hotel, her satisfaction is determined by her individual preference for the hotel and random noise in the service experience. The second equation indicates that a customer’s satisfaction in later encounters with the hotel is influenced by her satisfaction with the past experience. H1 suggests that \( \beta_1 \) is negative.

We next consider the influence of online service recovery. To assess the influence of service recovery effort on complaining customers, we create a dummy variable \( \text{ReceivedResponse}_{ijt-1} \) to indicate whether customer \( i \) has received online managerial response from hotel \( j \) for his/her previous online WOM posting. The dummy variable takes the value of 1 if the management responded to her prior posting and the value of 0 if not. We add the dummy variable to equation (2) to test H2a.

\[ \text{rating}_{ijt} = \begin{cases} 
\theta_{ijt} + \epsilon_{ijt}, & \text{if } t \text{ is the first time customer } i \text{ interacts with hotel } j \\
\beta_0 + \beta_1 \text{rating}_{ijt-1} + \beta_2 \text{ReceivedResponse}_{ijt-1} + \theta_{ij} + \epsilon_{ijt}, & \text{otherwise} 
\end{cases} \quad (3) \]

H2a indicates that customers who receive online service recovery will be more satisfied. We thus expect \( \beta_2 \) to be positive. H2b suggests that the influence of online service recovery is stronger for the most unsatisfied customers. To test the hypothesis, we create a new dummy variable \( \text{LowSatisfaction}_{ijt-1} \) to indicate that a customer has indicated the lowest rating in her previous review of the hotel:

\[ \text{LowSatisfaction}_{ijt-1} = \begin{cases} 
1, & \text{if } \text{Rating}_{ijt-1} = 1 \\
0, & \text{otherwise} 
\end{cases} \quad (4) \]

We then incorporate the interaction between the service recovery dummy variable and the low satisfaction dummy variable to assess whether online service recovery are more influential on the least satisfied customers. H2b suggests that the coefficient on the interaction term, \( \beta_3 \), be positive.

\[ \text{rating}_{ijt} = \begin{cases} 
\theta_{ijt} + \epsilon_{ijt}, & \text{if } t \text{ is the first time customer } i \text{ interacts with hotel } j \\
\beta_0 + \beta_1 \text{rating}_{ijt-1} + \beta_2 \text{ReceivedResponse}_{ijt-1} + \\
\beta_3 \text{ReceivedResponse}_{ijt-1} \times \text{LowSatisfaction}_{ijt-1} + \theta_{ij} + \epsilon_{ijt}, & \text{otherwise} 
\end{cases} \quad (5) \]

We next assess the influence of online service recovery on customers who observed the service recovery but did not receive service recovery themselves. To perform the test, we introduce a new dummy variable \( \text{ObservedResponse}_{ijt} \) to identify whether customer \( i \) had posted WOM on hotel \( j \) before time \( t \) and the hotel had provided service recovery to others but not to customer \( i \) by time \( t \). H3a suggests that the influence of online service recovery on other customers is negative due to peer-indicated fairness concerns. We thus include the dummy variable into equation (4) and expect the coefficient on the dummy variable \( \beta_4 \) is negative.

\[ \text{rating}_{ijt} = \begin{cases} 
\theta_{ijt} + \epsilon_{ijt}, & \text{if } t \text{ is the first time customer } i \text{ interacts with hotel } j \\
\beta_0 + \beta_1 \text{rating}_{ijt-1} + \beta_2 \text{ReceivedResponse}_{ijt-1} + \\
\beta_3 \text{ReceivedResponse}_{ijt-1} \times \text{LowSatisfaction}_{ijt-1} + \\
\beta_4 \text{ObservedResponse}_{ijt} + \theta_{ij} + \epsilon_{ijt}, & \text{otherwise} 
\end{cases} \quad (6) \]

Hypothesis 3b further suggests that the negative influence of online service recovery on customers who observe but do not receive service recovery is the highest for the most unsatisfied customers. To test the hypothesis, we include the
interaction term between observing service recovery effort and the dummy variable for low satisfaction into equation (5). Hypothesis 3b indicates that the coefficient should be negative.

\[ \text{rating}_{ijt} = \begin{cases} 
\theta_i + \epsilon_{ijt}, & \text{if } t \text{ is the first time customer } i \text{ interacts with hotel } j \\
\beta_0 + \beta_1 \text{Rating}_{ijt-1} + \beta_2 \text{ReceivedResponse}_{ijt-1} + \\
\beta_3 \text{ReceivedResponse}_{ijt-1} \times \text{LowSatisfaction}_{ijt-1} + \\
\beta_4 \text{ObservedResponse}_{ijt} + \\
\beta_5 \text{ReceivedResponse}_{ijt-1} \times \text{LowSatisfaction}_{ijt-1} + \theta_j + \epsilon_{ijt}, & \text{otherwise} 
\end{cases} \]  

(7)

DATA ANALYSIS

Results

Table 3 presents the results of the analysis. We take a step-wise approach and start with the analysis on how a customer’s past satisfaction influences her subsequent satisfaction with the same service provider. The result supports Hypothesis 1, suggesting that a customer’s past satisfaction negatively influences her future satisfaction with the same service provider. A customer with unsatisfactory past experience is more likely to have higher satisfaction in the future, while a customer with satisfactory experience is more likely to have lower satisfaction in the future. The result also offers an alternative explanation of the service recovery paradox. It suggests part of the satisfaction increase observed after service recovery may not be attributable to the effect of service recovery effort. Customers are likely to be more satisfied in the future after a service failure even without service recovery effort due to their lower expectation. It is thus necessarily to control for the mean reversion in customer satisfaction in assessing the influence of online service recovery effort.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Equation (2) Coefficients (std errors)</th>
<th>Equation (3) Coefficients (std errors)</th>
<th>Equation (5) Coefficients (std errors)</th>
<th>Equation (7) Coefficients (std errors)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant ($\beta_0$)</td>
<td>0.949*** (0.024)</td>
<td>0.945*** (0.024)</td>
<td>0.919*** (0.024)</td>
<td>0.926*** (0.024)</td>
</tr>
<tr>
<td>Rating$_{ijt-1}$ ($\beta_1$)</td>
<td>-0.239*** (0.006)</td>
<td>-0.239*** (0.006)</td>
<td>-0.236*** (0.006)</td>
<td>-0.238*** (0.006)</td>
</tr>
<tr>
<td>ReceivedRecovery$_{ijt-1}$</td>
<td>0.024** (0.010)</td>
<td>0.019** (0.010)</td>
<td>0.021** (0.010)</td>
<td>0.056** (0.010)</td>
</tr>
<tr>
<td>ReceivedRecovery$_{ijt-1}$ *</td>
<td>0.427*** (0.056)</td>
<td>0.388*** (0.056)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LowSatisfaction$_{ijt-1}$</td>
<td>(0.106)</td>
<td>(0.139)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ObservedRecovery$_{ijt-1}$</td>
<td></td>
<td></td>
<td></td>
<td>-0.008 (0.014)</td>
</tr>
<tr>
<td>ObservedRecovery$_{ijt-1}$ *</td>
<td></td>
<td></td>
<td></td>
<td>-0.244** (0.121)</td>
</tr>
<tr>
<td>LowSatisfaction$_{ijt-1}$ *</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-Square</td>
<td>98.33%</td>
<td>98.33%</td>
<td>98.33%</td>
<td>98.33%</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>316,567</td>
<td>316,567</td>
<td>316,567</td>
<td>316,567</td>
</tr>
</tbody>
</table>

Table 3: Analysis of Online Service Recovery on Customer Satisfaction

The influence of online service recovery on complaining customers is analyzed in Column 2 and 3 of Table 3. Column 2 assesses the average influence of online service recovery effort. The result reveals that online managerial responses have a positive but surprisingly modest impact on the satisfaction of customers who received them. Service recovery effort increases average customer satisfaction by a mere 0.02 on a 1-5 scale. The small increase, however, masks the significant impact of service recovery effort on the least satisfied customers. In Column 3, we allow the influence of online service recovery on customers with the lowest satisfaction to differ from other customers. The results show that receiving responses from a service provider significantly increases the satisfaction of the least satisfied customers. Specifically, the analysis shows that receiving responses increases customer satisfaction by 0.427 (on a 1-5 scale) for these customers, but only 0.019 for the rest of the customers. The results support Hypothesis 2b.

Column 4 assesses the influence of online service recovery on customers who observed recovery effort on others but did not receive it themselves. The result indicates that, on average, observing but not receiving managerial response has no influence on customer satisfaction, rejecting H3a. However, the insignificant result masks its significant and negative impact on customers who were most unsatisfied about their previous interaction with the service provider. For these customers, observing the service recovery effort on others reduces their satisfaction by 0.244 on a 1-5 scale. This result supports H3b.
Overall, our results support the performance-confirmation theory on customer satisfaction and suggest that online service recovery can improve customer satisfaction for the most unsatisfied customers but have limited influence on other customers. Moreover, we find that online service recovery negatively affect the most unsatisfied customers when they observe others receiving recovery effort but do not receive recovery effort 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 satisfaction.

**Robustness**

To validate the robustness of our analysis, we model customer satisfaction as discrete variables instead of continuous variables. This allows more flexibility in understanding how customers with different satisfaction level response to online service recovery. To perform the robustness analysis, we note that customer satisfaction for a hotel is calculated as the average rating of four underlying sub-ratings on cleanliness, environment, service and facility. As a result, the rating could be non-integer, which leads to a large number of rating levels. To making the analysis parsimony, we first round customer review ratings to integer numbers and then create corresponding dummy variables for each rating level. We use these dummy variables in place of the continuous customer satisfaction variable in equations (2), (5) and (7).

Table 4 reports the result for the robustness analysis. Column 1 analyzes the base model. The result again shows a clear pattern of mean reversion. It shows that customers with previous review rating of less or equal to 3 are more likely to increase their ratings in the next round of reviews, while customers with review rating 4 or 5 are more likely to decrease their ratings. The effect is particularly strong for customers in the lowest two rating levels. Their satisfaction level increases by 0.79 and 0.54 respectively. Column 2 reports the analysis about the impact of online service recover effort on complaining customers. It confirms that online service recovery can significantly improve future satisfaction of the most unsatisfied customers, but it has little influence on other customers. Column 3 reports the impact of online service recovery effort on customers who observe recovery effort to others but do not receive recovery effort themselves. The result again shows that the negative impact concentrates among the least satisfied customers. The observation of recovery effort has little influence on other customers. This result supports the argument for peer-induced fairness concerns.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Equation (2)</th>
<th>Equation (5)</th>
<th>Equation (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficients</td>
<td>Coefficients</td>
<td>Coefficients</td>
</tr>
<tr>
<td></td>
<td>(std errors)</td>
<td>(std errors)</td>
<td>(std errors)</td>
</tr>
<tr>
<td>Previous Rating = 1.0</td>
<td>0.794***</td>
<td>0.724***</td>
<td>0.814***</td>
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<tr>
<td></td>
<td>(0.059)</td>
<td>(0.066)</td>
<td>(0.073)</td>
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<td>Previous Rating = 2.0</td>
<td>0.538***</td>
<td>0.550***</td>
<td>0.505***</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.043)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>Previous Rating = 3.0</td>
<td>0.223***</td>
<td>0.215***</td>
<td>0.161***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Previous Rating = 4.0</td>
<td>-0.020***</td>
<td>-0.020***</td>
<td>-0.046***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Previous Rating = 5.0</td>
<td>-0.229***</td>
<td>-0.239***</td>
<td>-0.219***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.010)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>ReceivedResponse * Previous Rating = 1.0</td>
<td>0.373**</td>
<td>0.581**</td>
<td></td>
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<tr>
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<td>(0.152)</td>
<td>(0.155)</td>
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<td>0.100</td>
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<tr>
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<td>(0.096)</td>
<td>(0.084)</td>
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<tr>
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<td>0.052</td>
<td>-0.006</td>
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<td>(0.035)</td>
<td>(0.030)</td>
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<td>ReceivedResponse * Previous Rating = 4.0</td>
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<td>-0.017</td>
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<td></td>
<td>(0.016)</td>
<td>(0.015)</td>
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<tr>
<td>ReceivedResponse * Previous Rating = 5.0</td>
<td>0.042**</td>
<td>0.032*</td>
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<tr>
<td></td>
<td>(0.018)</td>
<td>(0.017)</td>
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<tr>
<td>ObservedResponse * Previous Rating = 1.0</td>
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<td>-0.359***</td>
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<tr>
<td></td>
<td>(0.131)</td>
<td>(0.131)</td>
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<tr>
<td>ObservedResponse * Previous Rating = 2.0</td>
<td>-0.072</td>
<td>0.046*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
<td>(0.067)</td>
<td></td>
</tr>
<tr>
<td>ObservedResponse * Previous Rating = 3.0</td>
<td>0.046*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.026)</td>
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</table>
Online service recovery is often the only tool available for service managers to address online customer complaints and to improve customer satisfaction and loyalty. However, little is known on how online service recovery influences customer satisfaction and how effective it is. This paper presents a systemic analysis of online service recovery and its impact on customer satisfaction. Based on expectation-confirmation theory and peer-induced fairness theory, this research reveals that 1) customer satisfaction follows a mean reversion process; 2) online service recovery effort is the most effective in improving customer satisfaction for customers with the lowest satisfaction level; and 3) observing online service recovery to others but not receiving it themselves has a significant and negative impact on future satisfaction of customers with the lowest satisfaction level.

The finding of this paper has implications for researchers on service management. Service recovery has been increasingly recognized as an important element of service management but research on service recovery is still evolving. Moreover, little is known on the effectiveness of online service recovery. In this study, we advance our understanding of online service recovery on two fronts. First, we find that online service recovery has unique characteristics due to its public nature. In particular, observing service recovery to others could have a significant impact on a customer’s satisfaction level. We show that our result is consistent with recent findings on peer-induced fairness and indicate that future research on service recovery shall consider the role of peer-induced fairness. Second, we highlight the importance of control for mean reversion in customer satisfaction over multiple interactions with a service provider. A common approach used in prior studies on service recovery is to compare customer satisfaction before and after service recovery. Our results show that part of the changes in customer satisfaction may not be due to service recovery effort. Rather, it is caused by changes in customer expectation which influences their future satisfaction.

The finding of this paper also has significant implications for service operators. First, our result highlights the value of online managerial response as a tool for service recovery. These managerial responses allow a service provider to communicate with the complaining customers and perform service recovery to improve their satisfaction. Second, we show that online customer complaints have distinctive characteristics not present in offline customer complaints due to its public nature. As a result, a service provider needs to be carefully in making service recovery effort to ensure that all complaining customers are addressed equitably. Third, this study helps service providers to make a better decision on how to use online service recovery in service operations. We show that online service recovery is highly effective among customers with the lowest satisfaction level but has limited influence on other customers. The result indicates that service operators shall reexamine their resource allocation strategy for online service recovery effort and focus their effort on the least satisfied customers.

This study also has a number of limitations. First, we are limited to customer satisfaction data and online service recovery data we retrieved from the service operator’s website. As a result, we do not have operational details about the nature of service failures and the service recovery processes. Survey studies or field studies will be valuable in the future to provide a more detailed model of the online service recovery process. Second, our focus is on customer satisfaction. Another important goal of service recovery is to improve customer loyalty and prevent customer exits. Due to data availability, we are not able to assess the effectiveness of online service recovery on customer loyalty and it will be valuable to analyze the relationship in future studies. Third, our analysis does not differentiate different types of service recovery effort which could vary in their impacts on customer satisfaction. It will be valuable for future studies to conduct content analysis and assess how the content of online service recovery effect influences customer satisfaction.

CONCLUSIONS AND IMPLICATIONS

Online service recovery is often the only tool available for service managers to address online customer complaints and to improve customer satisfaction and loyalty. However, little is known on how online service recovery influences customer satisfaction and how effective it is. This paper presents a systemic analysis of online service recovery and its impact on customer satisfaction. Based on expectation-confirmation theory and peer-induced fairness theory, this research reveals that 1) customer satisfaction follows a mean reversion process; 2) online service recovery effort is the most effective in improving customer satisfaction for customers with the lowest satisfaction level; and 3) observing online service recovery to others but not receiving it themselves has a significant and negative impact on future satisfaction of customers with the lowest satisfaction level.

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