MODERATING EFFECTS OF PRODUCT HETEROGENEITY BETWEEN ONLINE WORD-OF-MOUTH AND HOTEL SALES

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ABSTRACT

In online markets, Word-of-Mouth (WOM) plays a very important role in shoppers' online purchasing decisions, especially for experience goods. Hotels, as a form of service product, are intangible and cannot be evaluated before consumption, which makes WOM even more important. Several studies focus on the influence of online WOM on business performance. However, little attention has so far been paid to the asymmetric effect of WOM resulting from product heterogeneity in service industries. Hotel products can be classified by star ratings, with their services heterogeneous across different classifications. This study investigates the moderating effect of hotel star rating on the relationship between WOM and sales performance. To address the challenge of missing data, we conduct our empirical study using the difference-in-difference approach. Data about 1,689 hotels were collected from two major online travel agencies in China. We show that both the average rating of online WOM and rating variance have a significant impact on sales, and this effect is significantly moderated by hotel star rating. WOM has more impact on sales for hotels with lower rather than higher star ratings. The findings will help researchers and practitioners to understand more about the asymmetric impact of online WOM on service products.

Keywords: Online word-of-mouth; Service products; Product heterogeneity; Hotel rooms; Online sales

1. Introduction

Word-of-mouth (WOM) denotes informal communication among consumers about products and services [Liu 2006]. It has always been regarded as a powerful influence on consumer behavior [Anderson 1998; Mahajan et al. 1984], and this has now been enhanced through the rapid growth of Web 2.0 and social media [Utz et al. 2011]. With the popularity of online WOM activities, an increasing number of companies is offering online review services across various industries such as movies [Fattach 2001], online retailing [Dellarocas 2006], and television networks [Duan et al. 2008]. Tourism, particularly the hotel industry, is one of the fastest-growing areas of such activity [Ye et al. 2009; Yoo & Gretzel 2011]. TripAdvisor, one of the largest and most popular worldwide online travel communities, reports more than 50 million unique visitors per month, posting over 60 million reviews and opinions [Tripadvisor.com 2012].

Litvin et al. [2008] suggest that WOM is particularly important for experience goods like hotels. Hotel product offerings are intangible and cannot be evaluated before consumption, which makes interpersonal influence more important. The consumption of hotel products is also seen as high risk, so consumers tend to rely on the evaluation of a reference group to reduce this [Sparks & Browning 2011]. The hotel product is also seasonal and perishable, which forces consumers to rely on, and hence seek out, recent reviews [Dalbor & Andrew 2000]. WOM is also critical to hospitality marketers who operate in a highly competitive environment where interpersonal influence could become a source of advantage [Sparks & Browning 2011].

Several recent studies have explored the issue of online reviews in different industries, focusing on how WOM influences business performance. They conclude there is a direct positive relationship between online user ratings and product sales [Ye et al. 2009; Ye et al. 2011]. However, such work still cannot fully explain *how* user ratings affect sales. Product sales can be affected not only by internal factors such as quality, brand, and price, but also external factors such as consumer reviews, preferences, and the acts of other, homogenous competitors. Besides, while many researchers treat WOM as an exogenous factor that drives customers to make a purchase decision [Chen et al. 2004; Dellarocas et al. 2007], others emphasize that online WOM could also be the outcome of product sales [Reinstein & Snyder 2005; Duan et al. 2008], and suggest that the causality between the two should be analyzed in both directions [Duan et al. 2008]. The complicated interaction effects and endogeneity problems also call for a deeper understanding of how WOM influences firm performance in the context of other factors. For example, while Ye et al. [2009], looking at the effect of online WOM in the hospitality field, analyze how consumers' average ratings and rating variance affect hotel online bookings, they fail to take into account the endogeneity issue so as to separate the effect of online WOM from other observable factors such as hotel quality. Moreover, their model is cross-sectional, which may not control for intrinsic product heterogeneity, so their results could be unreliable.

Signaling theory proposes that people rely on signals whenever they have to make a judgment in conditions of uncertainty. Online shoppers usually encounter even higher information asymmetry about the quality of products, since they are not making a purchase face to face with the seller [Park & Lee 2009]. Different sources of information are normally used by online shoppers in the purchasing process, including online WOM and traditional offline information like product heterogeneity and so on. In the hotel industry, star rating is an important piece of information about product heterogeneity. WOM and other available information will all provide signals to reduce information asymmetry. How WOM interacts with other product heterogeneity information in the purchasing process is still largely unknown, especially for experience goods such as hotel rooms.

Given the limitations of previous work, this study has two main goals. Firstly, we explore how offline information, namely hotel star rating, affects the relationship between online customer reviews and sales by accounting for the endogenous effect of managerial expertise. Secondly, we examine the relationship between online reviews and hotel sales performance. In a departure from the extant WOM literature, which focuses on the average inclination of reviews, we also look at how the variance of customer opinion affects hotel sales. This is a topic on which no consensus has yet been reached. We collect hotel information and customer reviews from two major online travel agencies in China, Ctrip.com (Ctrip) and Elong.com (Elong), and refine the final data to include 1,689 hotels over a 24-month period. The two major challenges involved in such an analysis are: (1) unobservable factors such as management expertise, unstable price variation over time, and competitor strategies may influence hotel sales but cannot be easily measured; and (2) it is difficult to get private booking data from hotels, since this information is considered highly confidential and is not usually accessible to outsiders. To solve the first problem, we use a difference-in-difference approach with panel data to eliminate unobservable factors as well as the endogenous effect. To tackle the second, we follow the approach adopted in previous work [Ye et al. 2008; Ye et al. 2009; Ye et al. 2011] and use the monthly number of reviews as a proxy for online hotel bookings.

The rest of this paper is organized as follows. After briefly reviewing the WOM literature, we propose the research hypotheses and build our empirical models. Using data collected from the two online travel agencies, we then present the statistical results and findings. The paper concludes with a review of the theoretical and managerial implications of our results, and a discussion of the limitations of this study and future research directions.

2. Literature Review and Hypotheses

Online WOM is a useful tool for customers to reduce perceived risk by searching for information before buying new products [Srinivasan & Ratchford 1991, Zhu & Zhang 2010]. After a purchase has been made, online WOM also offers an easy and convenient way for consumers to comment on their acquisitions, complain about their dissatisfaction, share details with friends, or even argue with vendors. Companies also regard WOM as a positive and effective marketing tool through which to execute business strategies [Litvin et al. 2008]. Some businesses regularly post product information online and sponsor promotional events in online communities [Mayzlin 2006]; others issue managerial responses to mollify unhappy consumers [Ye et al. 2008], or even manipulate online reviews strategically to influence purchase decisions [Dellarocas 2006].

From an early stage, studies of WOM have focused on examining how customer reviews influence peers and, in turn, sales [Cheung et al. 2009; Chevalier & Mayzlin 2006; Li & Hitt 2008; Senecal & Nantel 2004]. Others examine the value of various metrics of online review content in influencing and predicting future sales [Chen et al. 2004; Clemons et al. 2006; Dellarocas et al. 2007; Duan et al. 2008; Goldstein & Goldstein 2006; Liu 2006; Park & Kim 2008]. Some of the findings are interesting and indeed inspiring. For instance, Sorensen and Rasmussen [2004] look at the impact of New York Times reviews on book sales, and show not only that positive reviews have more

impact than negative ones, but also, and somewhat surprisingly, that negative reviews also have a positive impact on sales. However, their product dataset of 173 hardcover fiction releases is relatively small, and the authors also acknowledge that their findings may be specific to the book market [Sorensen & Rasmussen 2004]. In the hospitality field, Ye et al. [2011] show that hotels with higher average ratings take more bookings. They create a log-linear regression model using a total of 40,424 reviews from 1,639 hotels. Considering the number of average reviews for each hotel is relatively small and the influence of time is not included, this relationship is worthy of reconsideration in the hotel industry context.

Although a considerable body of research uses regression models to study the positive impact of WOM on firm performance in various fields, the endogeneity of WOM has not been addressed. In a statistical model, endogeneity exists when there is a correlation between the variable and the error term. In a typical regression model, the dependent variable has an interactive effect on the independent variable. Sometimes, however, the dependent variable may have a feedback effect on the independent variable. In hotels, managerial expertise makes multiple contributions to performance. On the one hand, hotels with better management are more likely to obtain positive reviews from consumers, resulting in higher ratings. On the other hand, consumers will prefer better-run hotels, so their bookings will be higher than those with poorer management. Although managerial expertise is an essential part of corporate operations, it is not easy to capture due to its intangible features. It is often treated as an error factor in regression models. Accordingly, its endogenous effect on hotel sales may influence the explanation of the WOM effect. Nowadays, many hotels run their business through multiple online travel agents simultaneously and allow consumers to make reservations through all of them. It is reasonable to assume the managerial expertise of each hotel will be consistent across different online travel agents. Thus, using the difference-in-difference approach, we compare online bookings for the same hotels across two online travel agents to cancel out the effect of hotel managerial expertise, and hence reexamine the effect of consumer reviews on bookings.

Online reviews have two effects on customers' booking decisions, namely the awareness effect and persuasive effect. The awareness effect improves customers' cognitive load toward hotels by reading others' reviews [Alba & Chattopadhyay 1986], while the persuasive effect of reviews encourages them to make the decision eventually. Most risk-averse customers tend to choose hotels with the most compliment and favored by others. The rating of customer reviews is an important measurement of their sentiment polarity. A higher rating of customer review usually represents higher satisfaction and better hotel quality, which also reduces their risk of selection. It is reasonable to conclude that positive hotel reviews will enhance their inclusion in consumers' awareness sets, leading to higher sales. Therefore, we hypothesize:

H1: The average rating of customer reviews will have a positive effect on hotel sales.

Although the average rating of customer reviews of a hotel provides an indication of general performance based on past experience, there may not be enough attributes present to reflect all the necessary information [Berger et al. 2010]. Berger et al. [2010] suggest that products which have been reviewed have a better chance of catching the attention of customers than those which have not, even if the review itself gives a bad impression. Furthermore, even for a product with good reviews, some negative comments may be present that are important for certain consumers, restraining their purchase decisions. Since consumers may have different opinions of the same product, we assume that it is necessary to look into the variance of reviews as well as the average rating.

Compared with average ratings, research on the variance of customer reviews is limited, and the results inconsistent. Using data from Ratebeer.com, a popular beer review website, Clemons et al. [2006] show that the variance of ratings for a new beer product positively enhances its sales. They explain that rating dispersion reflects customers' preferences towards a product type. Products with extreme reviews have more chance of being bought than those that are merely liked by customers. In contrast, Ye et al. [2011] find there is no significant relationship between the variance of review ratings and hotel sales. They suggest customers tend to take the overall opinion of a hotel into account when making a booking. Their data was collected from a Chinese travel agent during 2007-2008, so in the light of the fast growth of the online travel agent market in China, we will update the data source and research proposition.

Customers usually get relatively less information about hotels from limited resources, comparing to other experience goods such as books and movies. Others' reviews posted on the online travel agency becomes a major source, and customers try to make the best use of these reviews. Reviews reflect not only hotel quality but also reviewers' preferences and needs. With more hotel reviews being posted, customers are able to obtain more information, which inevitably leads to discrepancies. Although inconsistent opinions may confuse the decision-making process, they may also increase the cognitive load of future customers, so they can choose hotels based on demand. For example, if a hotel is very close to the traveler's destination and he doesn't care about its old facility, he may give a positive review to this hotel. If another traveler cares about hotel facilities more than its location, he may not book this hotel after reading this review. Similarly, even negative reviews can attract potential customers

according to their preferences and needs. Especially for hotels that are not well-known, more information - both positive and negative, will reduce the risk of booking hotels. More dispersed reviews will help customers be more aware of the hotel from a variety of angles, which may lead to more sales. On third-party travel websites, many hotels are less well known to customers, so we assume the variance of customer ratings will play an influential role in increasing awareness and hence improve hotel sales. We therefore hypothesize:

H2: The variance of customer reviews will have a positive effect on hotel sales.

Signaling theory proposes that people search for referential information (as signals) when they have to make a decision in conditions of uncertainty. Vermeulen and Seegers [2009] argue that well-known hotels have a stronger link to consumers and this is less affected by exposure to reviews. Therefore, the informative effect of online reviews will be stronger for lesser-known hotels. They define well- and less-known hotels by asking 168 participants if they are familiar with their names. This method is easy to use but may also introduce bias, because it depends on respondents' knowledge and experience. Star rating can be a more reliable signal, since it is an official standard that distinguishes the quality of the infrastructure, facilities, and services provided by hotels. Also, it is relatively objective, compared with other information provided on a hotel webpage. Lastly, it is also related to price, which means customers have to trade off quality against expenditure. It is easy for customers to predict that a five-star hotel could offer him good facility and service, even if he is not familiar with its brand. In another case, although a five-star hotel has several negative reviews, customers may still feel confident that it has better quality than a three star hotel with higher average rating. Because star rating itself provides additional information, the WOM effect will be weakened. Since customer cannot get quality guaranteed from low star rating hotels, other customers' reviews have significant informative and persuasive effect. Usually, customers rate their stay based on comparison between expectation and gain, rather than the quality solely. Thus, low star rating hotels may also have positive reviews, which will affect customers who are longing for a reasonable price. It is reasonable to conclude that star ratings will influence customers' booking decisions, but will play a moderating rather than a direct role. Since consumers generally have less information about lower-rated hotels, customer reviews of these establishments should be more helpful and informative than those of hotels with higher star ratings. We therefore hypothesize:

H3: The average ratings of customer reviews will have a stronger effect on hotels with lower than those with higher star ratings.

Additionally, Bone [1995] finds the effect of WOM is greater in a disconfirming situation, using an offline experiment. Our research differs from this work in that (1) we extend the research to an on- rather than offline context, and (2) Bone defines the disconfirming situation as the contradiction between the experimenter's expectation of product performance and other reviewers' verbal opinion, whereas we focus on the limited resource of product information.

3. Methodology
3.1. Empirical Model

A key task of this study is to develop an empirical model to measure the influence of star rating and customer ratings on hotel bookings, while controlling for the influence of managerial expertise and other motivating factors unobservable by the researchers. Online customer reviews differ from offline WOM in that they are available to all customers all the time, and new reviews can be added at any point. Most visitors regard recent reviews as more valuable because they reflect the hotel's current status. It is therefore more appropriate and accurate to construct a model that can separate time periods. We thus propose the following models.

For hotel i at travel agency j in month t:

$$HotelSales_{it}^{j} = \mu^{j} + \nu_{i} + \beta_{1}RatingAvg_{it}^{j} + \beta_{2}RatingVar_{it}^{j} + \beta_{3}Mgt_{it} + X_{it}\Gamma + \varepsilon_{it}^{j} \quad (1)$$

In the model, μ^{j} represents the fixed effect for travel agency j, and ν_{i} represents the fixed effect for hotel i. $RatingAvg_{it}^{j}$ denotes the ratings that customers give hotel i during period t. Since the customer rating is shown on the webpage of each hotel and can be read by all future customers, we treat it as a status variable. The subscripts it and superscript j indicate that the ratings customers give each hotel on either site are unique and can be different depending on their own experience and consideration; besides, they will change over time. Mgt_{it} represents hotels' underlying expertise in managing properties, developing a marketing strategy, and delivering services which will satisfy customers. This could also change over time for each hotel, which is reflected in the superscript it. Furthermore, there is no superscript j, because we assume that for each hotel i, its managerial expertise will be consistent across each travel agency website, the rationale of which will be discussed in the Data session. X_{it}

includes all other unobserved, time-varying, and hotel-specific factors that influence reviews and sales. The objective of the analysis is to identify β_1 and β_2, the influence of average customer ratings and their variance on sales. Since customer rating is correlated with hotels' managerial expertise and this is difficult to observe, equation (1) cannot be estimated directly and accurately.

To solve this problem, we use a difference-in-difference approach to cancel out the influence of hotels' managerial expertise and other unobserved factors, and identify the influence of customer ratings on sales. Based on our assumptions, the relevant equation is as follows:

$$HotelSales_{it}^{j} - HotelSales_{it}^{j'} = (\mu^{j} - \mu^{j'}) + (\varepsilon_{it}^{j} - \varepsilon_{it}^{j'}) + (\beta_1 RatingAvg_{it}^{j} - \beta_1' RatingAvg_{it}^{j'}) + (\beta_2 RatingVar_{it}^{j} - \beta_2' RatingVar_{it}^{j'}) \quad (2)$$

As equation (2) shows, the difference-in-difference approach cancels out not only unobserved managerial expertise but also other hotel-specific variables that may change over time such as competitor strategies and star ratings. When collecting the data for this study, we find that the price of each hotel is the same across the two websites, so this variable can be canceled out as well.

To test the moderating role of star rating, we introduce a variable which measures this. Its value equals hotels' official star rating and its value is set to 0 for those without one. Equation (1) is thus refined as follows:

$$HotelSales_{it}^{j} = \mu^{j} + \nu_i + \beta_1 RatingAvg_{it}^{j} + \beta_2 RatingVar_{it}^{j} + \beta_3 RatingAvg_{it}^{j} \times Star_i + \beta_4 RatingVar_{it}^{j} \times Star_i + \beta_5 Mgt_{it} + X_{it}\Gamma + \varepsilon_{it}^{j} \quad (3)$$

Similarly, we apply the difference-in-difference approach, so the model is modified as in equation (4):

$$HotelSales_{it}^{j} - HotelSales_{it}^{j'} = (\mu^{j} - \mu^{j'}) + (\varepsilon_{it}^{j} - \varepsilon_{it}^{j'}) + (\beta_1 RatingAvg_{it}^{j} - \beta_1' RatingAvg_{it}^{j'}) + (\beta_2 RatingVar_{it}^{j} - \beta_2' RatingVar_{it}^{j'})$$
$$+ (\beta_3 RatingAvg_{it}^{j} \times Star_i - \beta_3' RatingAvg_{it}^{j'} \times Star_i) + (\beta_4 RatingVar_{it}^{j} \times Star_i - \beta_4' RatingVar_{it}^{j'} \times Star_i) \quad (4)$$

Another challenge we encounter is the difficulty of obtaining hotel online sales data directly. Other studies have used sales rankings as a proxy for actual sales [Chevalier & Mayzlin 2006; Ghose & Ipeirotis 2007]. Since Ctrip.com has a policy that only customers who have already booked and stayed in a hotel are allowed to post a review, Ye et al. [2009] use the number of reviews as a proxy for bookings and test its availability afterwards. Following their approach, we use the number of reviews on both websites to measure hotel sales. Equations (3) and (4) are hence refined as follows:

$$Ln(NumReview_{it}^{j}) - Ln(NumReview_{it}^{j'}) = (\mu^{j} - \mu^{j'}) + (\varepsilon_{it}^{j} - \varepsilon_{it}^{j'})_i$$
$$+ (\beta_1 RatingAvg_{it}^{j} - \beta_1' RatingAvg_{it}^{j'}) + (\beta_2 RatingVar_{it}^{j} - \beta_2' RatingVar_{it}^{j'}) \quad (5)$$

$$Ln(NumReview_{it}^{j}) - Ln(NumReview_{it}^{j'}) = (\mu^{j} - \mu^{j'}) + (\varepsilon_{it}^{j} - \varepsilon_{it}^{j'})$$
$$+ (\beta_1 RatingAvg_{it}^{j} - \beta_1' RatingAvg_{it}^{j'}) + (\beta_2 RatingVar_{it}^{j} - \beta_2' RatingVar_{it}^{j'})$$
$$+ (\beta_3 RatingAvg_{it}^{j} \times Star_i - \beta_3' RatingAvg_{it}^{j'} \times Star_i)$$
$$+ (\beta_4 RatingVar_{it}^{j} \times Star_i - \beta_4' RatingVar_{it}^{j'} \times Star_i) \quad (6)$$

A brief description of the variables is shown in Table1.

Table 1: Description of Variables

Variable Name	Description
$NumReview_{it}^{Ctrip}$	The number of reviews published on Ctrip for hotel i in month t
$NumReview_{it}^{Elong}$	The number of reviews published on Elong for hotel i in month t
$RatingAvg_{it}^{Ctrip}$	The average customer rating posted on Ctrip for hotel i in month t
$RatingAvg_{it}^{Elong}$	The average customer rating posted on Elong for hotel i in month t
$RatingVar_{it}^{Ctrip}$	The variance of the customer rating posted on Ctrip for hotel i in month t
$RatingVar_{it}^{Elong}$	The variance of the customer rating posted on Elong for hotel i in month t
$Star_i$	Official star rating of hotel i

3.2.   Data

Our data were retrieved from two travel agency websites, Ctrip (NASDAQ: CTRP) and Elong (NASDAQ: LONG). These are the two largest online travel agencies in Mainland China, both of which were founded in 1999. Ctrip is the dominant company in the Chinese online travel agency market, with a market share of 41.0%, compared to Elong's 7.0% [Iresearch 2011]. Both websites encourage their customers to post comments and rate their hotels after checking out. To encourage such submission, they also send email reminders with embedded links to each customer. They have also developed promotional programs to reward customers who write reviews. Unlike many other online review platforms, these sites only allow customers who have booked via their websites and checked out of the hotel successfully to post reviews, which is one of the reasons for selecting them as our data sources.

As mentioned earlier, we define hotel managerial expertise as how hotels manage their online business on travel agencies. These business activities include how they manage the layout of hotel webpage, make promotion strategy, adjust room rates timely and etc. The hotel webpage provides basic information, such as a summary about hotel history, location, transportation, facilities and services, and customers can take their first glance of the hotels through the photos displayed on the webpage. We observed that the information is very similar cross these two agencies. Hotels make their promotion strategies by providing coupons or cash back on the agencies, and adjust the daily room rates according to the market fluctuation. Considering Ctrip and Elong are the two largest and most popular travel agencies in China, it is reasonable to assume hotels endeavors to attract as many customers as possible. There may be occasions that they differentiate these business activities across these two agencies, but from a longitude view across all hotels, this difference could be balanced out. Thus, we assume the effect of hotel managerial expertise can be completely cancelled out in the difference-in-difference model.

We designed two crawlers using Java and used a program named LocoySpider to collect the data. For each hotel, we collected basic information such as official star rating, phone number, and room price (lowest single/standard room on the booking webpage), and review-related information such as number of reviews, customer ratings, and dates of published reviews. We selected hotels in nine major cities in China, namely Shanghai, Beijing, Shenzhen, Suzhou, Tianjin, Chongqing, Hangzhou, Wuxi, and Qingdao. We carried out the data collection over the period December 2009 till November 2011 for all hotels, and then aggregated the information on a monthly basis for the analysis.

Ctrip and Elong use different rating systems. Ctrip has a five-point rating framework where customers score the hotel for cleanliness, service, facilities, and environment, and the system then generates an average. Elong has a simplified recommendation system. Registered customers can "recommend" or "not recommend" a hotel as well as writing more detailed comments, while unregistered customers can comment but not give a recommendation. Due to these different rating systems, we rescored the semantic polarity of reviews on both sites to ensure data coherency. We developed a Java program using LingPipe and chose the Dynamic Language Model classifier with N-grams (n=8) to build the polarity classifier. We manually labeled 300 positive and 300 negative reviews to build the training set. Then, we trained the classifier and evaluated it with another 1,000 reviews. The accuracy of this classifier was 80.2%. We then used it to label all the reviews collected. Each review with a positive polarity was assigned a score of 1 and with a negative polarity a score of 0.

To apply the difference-in-difference approach, we have to match hotels across the two websites. Although many hotels register with both sites, they may do so under different domain names. To solve this problem, we matched hotels using their phone numbers. We also developed a program using an approximate string-matching technique called SecondString to match hotels with their names. The results showed that the former method has better accuracy.

We also filtered out hotels opened after 2009 using the open-year information provided by Ctrip. In total, we obtained valid data on 1,689 hotels, with 243,078 customer reviews from Ctrip and 213,638 from Elong.

A summary of the dataset is shown in Table 2. As can be seen, although there are more hotels on Elong, the total number of reviews on Ctrip is larger, demonstrating that customers can access more reviews for some hotels on Ctrip than on Elong.

Table 2: Summary of Dataset

	Ctrip	Elong
Number of cities selected	9	9
Number of hotels covered	5,434	5,955
Number of reviews collected	615,986	547,543
Number of matched hotels	1,689	1,689
Number of reviews of matched hotels	243,078	213,638

Research suggests that recent reviews influence customers more than older ones [Dellarocas 2003] and most customers read no more than the first two pages of text comments [Pavlou & Dimoka 2006]. This means reviews on the first two pages are more useful and influential when potential consumers are making a booking decision. Ctrip displays 15 and Elong 20 reviews per page. Therefore, for each review on Ctrip and Elong, we calculated the average rating and rating variance using the most recent 30 and 40 reviews, respectively. Then, we computed the average ratings posted for that hotel and their variance in each month to reflect the average option and its monthly variance.

We also noted that not all hotels have star ratings. According to China's hotel rating classification and evaluation policy, the criteria are based on two attributes; hotel facilities and operational quality. For hotel facilities, the China National Tourism Administration (CNTA) uses a detailed scoring system for each star category, with a total of 600 points available. The required scores to earn a star rating are 220 points for 3 stars, 320 for 4, and 420 for 5. There are no scoring cutoffs for one to two stars. The rating of operational quality for each hotel is converted into a percentage based on a preset standard established by the CNTA. The required percentages are 75% for 3 stars, 80% for 4, and 85% for 5. Again, there is no specific requirement threshold for one to two stars. The application of the star-rating process is voluntary, so certain lower-quality hotels may not participate given that the process is costly and time consuming. In our dataset, 71.8% of hotels had no star rating. The average rating of the remainder was 3.89. The distribution of star ratings is shown in Table 3.

Table 3: Distribution of Hotel Star Ratings

	Frequency	Proportion
No stars	1,213	71.8%
Two stars	23	1.4%
Three stars	143	8.5%
Four stars	179	10.6%
Five stars	131	7.8%
Total available hotels	1,689	100%

We analyze customer ratings across different hotel star ratings based on Ctrip data, as shown in Figure 1.
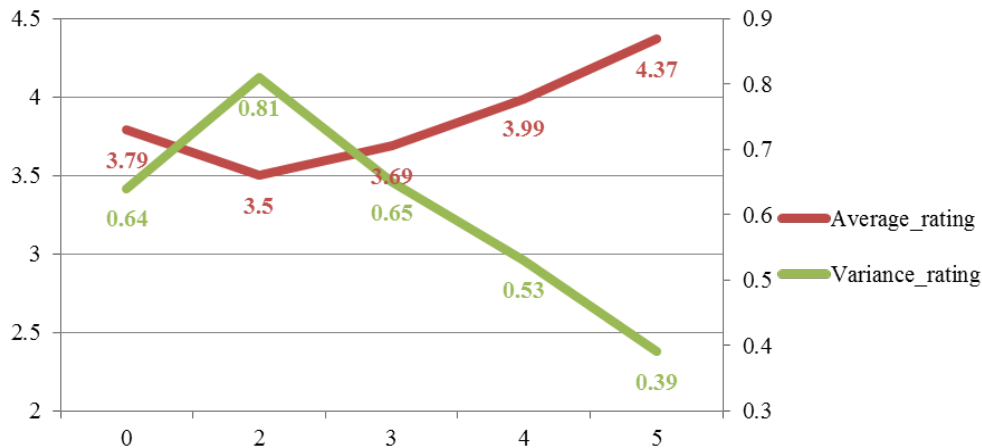

Figure 1: WOM across Different Hotel Star Ratings on Ctrip

Since Ctrip allows customers to rate their stays for booked hotels, we calculate the average value and variance value with numerical customer ratings instead of review polarity for each hotel. Then, we aggregate these scores by star rating. In Figure 1, the red line represents average customer ratings for hotels across different hotel star ratings, with the scores on the left Y-axis, and the green line represents the variance of customer ratings for hotels across different hotel star ratings, with the scores on the right Y-axis. As it shows, for hotels with star ratings (from two- to five-star), the trend of average scores appears to increase steadily with star rating, while for hotels without a star rating, the average score falls between that of three- and four-star properties. Unlike average customer ratings, the variance of customer ratings appear much lower on four-star and five-star hotels, and higher on two-and three-star hotels as well as no-star hotels. Part of the reason high star-rated hotels receive higher ratings might be that these

hotels provide better-quality facilities and service, which is more likely to lead to satisfaction consistently. However, higher expectations may also cause more dissatisfaction when not met, leading to a higher chance of negative reviews. For hotels without a star ratings, even though customers may have lower expectations for their consumptions, they could be delighted or disappointed by the actual outcomes, which causes a larger dispersion of customer ratings, which is worthy of further investigation.

3.3.   Statistical Results

We used Stata 10 to analyze the refined data using the random effect model. We firstly tested the relationship between customer reviews and hotel sales without the moderating variable. The estimation results of equation (5) are shown in the first column of Table 4. To clarify, we entered the regression models with the negative form of Elong coefficients, so we could directly compare the coefficient results between Ctrip and Elong.

As expected, both the average rating of customer reviews and their variance are positively related to the number of reviews on both Ctrip and Elong. However, the coefficient values of $RatingAvg$ and $RatingVar$ are quite different across the two sites. It can be seen that the average rating of reviews on Ctrip has more influence on sales, while the rating variance on Elong plays a more important role. One possible explanation for this could be that Ctrip provides more reviews per page for each hotel than Elong, as shown in Table 2. The inclusion of more reviews for each hotel thus provides more reliable information for evaluation purposes. As such, customers will prefer hotels with higher ratings on Ctrip, while on Elong customers will make their decision with the help of both positive and negative reviews. The results show that hotel sales improve when they get higher average ratings and higher rating variance. Therefore, H1 and H2 are both supported.

We then tested the moderating effect of hotel star rating. The results are shown in the second column of Table 4. The coefficients of the average customer rating and rating variance for Ctrip and Elong are also significantly positive, consistent with the first column. The coefficients of $RatingAvg_{it}^{Ctrip} \times Star_i$ and $RatingAvg_{it}^{Elong} \times Star_i$ are -0.0478 and -0.0462 respectively, indicating that star rating has a negative moderating effect. A similar effect can be seen on the relationship between review variance and hotel sales for Elong, but not Ctrip. In other words, the higher the hotel star rating, the less influence the average customer rating has on bookings across both sites, and the less influence customer rating variance has for hotels on Elong. As discussed above, the impact of rating variance on hotel sales is smaller than that of the average customer rating on Ctrip, and this is even smaller than it is on Elong. This could be the reason for $RatingVar_{it}^{Ctrip} \times Star_i$ being insignificant. The results show that customer reviews are particularly important for hotels with a lower star rating. Thus, H3 is also supported.

In this research, we focus mainly on the effect of reviews and star ratings without considering other factors that influence hotel operation and customer choice. This may explain the relatively low explanatory power of these models, as reflected in the R^2 values.

4.   Validation and Extension

To validate the robustness of our analysis, we conduct robustness checks by separating the WOM effect on hotel online bookings across different star ratings. This allows a better understanding of how customer ratings affect different levels of hotel. It should be noted that although hotels with the same star rating could be strong competitors, they may be affected by other hotels with different star ratings. It is rational to assume a customer chooses a 4-star hotel over a 5-star hotel if the 4-star hotel is closer to the customer's destination. In other words, the error terms in the regression models for each star rating category can be correlated, and it may cause bias if these regression models are analyzed separately. So we conduct a Seemingly Unrelated Regression (SUR) model to eliminate the interaction of error terms across different star ratings. The SUR model consists of five equations as shown in Equation (7), with m represents hotel star ratings of 0 and 2-5. As Table 5 shows, WOM has the strongest impact on online bookings for hotels with no star (1.1109 and 0.8139, respectively) and the weakest impact for hotels with five stars (0.9397 and 0.5277, respectively). The moderating effect on Elong hotels gets weaker as hotel star rating increases, but not steady and significant for Ctrip hotels. These results are consistent with our previous findings.

$$Ln(Num\,\mathrm{Re}\,view_{it,star=m}^{j}) - Ln(Num\,\mathrm{Re}\,view_{it,star=m}^{j'}) = (\beta_1 RatingAvg_{it,star=m}^{j} - \beta_1' RatingAvg_{it,star=m}^{j'})$$
$$+ (\beta_2 RatingVar_{it,star=m}^{j} - \beta_2' RatingVar_{it=star=m}^{j'}) \quad (7)$$
$$+ (\mu^j - \mu^{j'}) + (\varepsilon_{it,star=m}^{j} - \varepsilon_{it,star=m}^{j'})$$

Table 4: Results of Empirical Models

Independent Variable	Dependent Variable	Dependent Variable
$RatingAvg_{it}^{Ctrip}$	1.1065*** (0.0353)	1.1483*** (0.0378)
$RatingAvg_{it}^{Elong}$	0.7902*** (0.0299)	0.8201*** (0.0341)
$RatingVar_{it}^{Ctrip}$	0.7855*** (0.1016)	0.8072*** (0.1140)
$RatingVar_{it}^{Elong}$	2.5895*** (0.0936)	2.8372*** (0.1083)
$RatingAvg_{it}^{Ctrip} \times Star_i$		-0.0478*** (0.0184)
$RatingAvg_{it}^{Elong} \times Star_i$		-0.0462*** (0.0180)
$RatingVar_{it}^{Ctrip} \times Star_i$		0.0058 (0.0535)
$RatingVar_{it}^{Elong} \times Star_i$		-0.2839*** (0.0539)
Constant	-0.0414 (0.0330)	-0.0635** (0.0332)
Number of Observations	40,536	40,536
Number of Groups	1,689	1,689
R^2	0.0961	0.1040

*** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%

We also extend our study by conducting a week-based analysis to reduce the seasonality issue. Hotel sales can be affected by seasonal factors [Peers et al. 2012]. For example, holidays such as Christmas and New Year usually generate a sales peak in the month of December. Some travel destinations are more popular in summer or winter than other period of the year. Thus, it is hard to distinguish whether the intermissive increase in sales is due to customer reviews or seasonal effect. Prior research suggests using higher-frequency data can significantly reduce such effect [Non et al. 2003]. Thus, we aggregate the monthly data into weekly data and reexamine our models. As shown in Table 6, the results are consistent with our findings. Hotel sales are positively related with customer ratings and their variance. The effects of average ratings are more effective on hotels with lower star ratings.

Table 5: Effect of WOM on Hotel Online Bookings across Different Star Ratings

Independent Variable	Dependent Variable Star=0	Dependent Variable Star=2	Dependent Variable Star=3	Dependent Variable Star=4	Dependent Variable Star=5
$RatingAvg_{it}^{Ctrip}$	1.1109*** (0.0284)	0.7519*** (0.0304)	0.7483*** (0.0296)	1.0329*** (0.0329)	0.9397** (0.0389)
$RatingAvg_{it}^{Elong}$	0.8139*** (0.0291)	1.2243*** (0.0309)	0.7113*** (0.0280)	0.7455*** (0.0314)	0.5277*** (0.0387)
$RatingVar_{it}^{Ctrip}$	0.7916*** (0.0921)	0.1818** (0.0873)	0.3361*** (0.0915)	0.0893 (0.0977)	1.9269*** (0.1005)
$RatingVar_{it}^{Elong}$	2.8565*** (0.0919)	2.1979*** (0.0816)	2.1224*** (0.0890)	1.3172*** (0.0925)	1.8821*** (0.1114)
Number of Observations	40,536				
Number of Equations	5				

*** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%

Table 6: Results of Empirical Models based on Weekly Data

Independent Variable	Dependent Variable	Dependent Variable
$RatingAvg_{it}^{Ctrip}$	0.1941*** (0.0034)	0.2077*** (0.0039)
$RatingAvg_{it}^{Elong}$	0.0868*** (0.0031)	0.0905*** (0.0037)
$RatingVar_{it}^{Ctrip}$	0.0783*** (0.0108)	0.0746*** (0.0126)
$RatingVar_{it}^{Elong}$	0.4938*** (0.0091)	0.5519*** (0.0110)
$RatingAvg_{it}^{Ctrip} \times Star_i$		-0.0586*** (0.0110)
$RatingAvg_{it}^{Elong} \times Star_i$		-0.0199*** (0.0097)
$RatingVar_{it}^{Ctrip} \times Star_i$		0.0677 (0.0349)
$RatingVar_{it}^{Elong} \times Star_i$		-0.2922*** (0.0287)
Constant	0.0210*** (0.0037)	0.0182*** (0.0038)
Number of Observations	258,417	258,417
Number of Groups	1,689	1,689
R^2	0.0497	0.0528

*** denotes significance at 1%, ** denotes significance at 5%, * denotes significance at 10%

5. Implications

The main theoretical implications of this research relate to the closure of the knowledge gap about the moderating role of hotel star rating in the relationship between online WOM and hotel sales. Star rating is an important feature in consumer purchase decisions. Since making a hotel booking involves a tradeoff between quality and expense, the impact of ratings on customer decisions is worth studying. Our findings show that online WOM is more influential for hotels with lower than those with higher star ratings. We have also used a difference-in-difference approach with panel data to compare two Chinese online travel agency websites by eliminating unobserved factors, which had led to a better understanding of how WOM affects hotel sales. Our findings can be extended to related areas and open up numerous avenues for future research in hospitality and tourism management.

This study has also generated valuable implications for hospitality and tourism practitioners. Firstly, the importance of online WOM should be emphasized. In the online context, it helps travelers to gather information and suggestions from all kinds of sources, positive and negative, leading to a final consumption decision. Business practitioners also have more chance to "meet" consumers from all over the world using online channels. Small companies and start-ups are on the same footing as their larger competitors. As our results show, the impact of online reviews is even stronger for hotels with low star ratings. Price should not be their only advantage; client satisfaction as communicated through online WOM will attract more customers and increase future revenues. Secondly, practitioners should encourage customers to post online reviews and develop their strategies accordingly. As Yoo and Gretzel [2008] point out, most review writers want to help travel-service suppliers and to express their concern for other consumers. This is therefore a good opportunity for service providers to become more aware of consumers' needs and obtain their feedback. Hotels with lower star ratings should pay more attention to reviews, because this can generate good publicity. Thirdly, hotels should develop marketing strategies for how to respond effectively to consumer reviews. Some companies are developing service-recovery mechanisms to placate dissatisfied customers. For example, Ctrip.com provides a function for hotel managers to respond to reviews by explaining their operations and encouraging repurchase. Since such a response can be read by all customers, it helps to build trust and reputation. This mechanism has proved to be helpful to those hotels that are actually using it [Ye et al. 2008].

6. Conclusions and Limitations

With the growing popularity of consumer advice websites and services, virtual communication among online users has become commonplace. Although researchers have reached a consensus that having more positive customer reviews helps firms improve performance, little is yet known about the impact of discrepant reviews and other factors that may affect this process, such as star ratings in the context of the hotel industry. Using a difference-in-difference approach with data from two online travel agencies, this paper has reached the following conclusions. Firstly, we have shown that star rating plays a moderating role on the effect of customer reviews on hotel sales. To be more specific, the effect of reviews is stronger for hotels with lower than higher star ratings. Star ratings provide extra information about hotels and enhance customer awareness, so that the impact of review data is weakened. Secondly, both the valence and variance of online reviews have a significant impact on online hotel sales, since reviews reduce uncertainty and risk. With less cognitive load and more awareness, sales can be improved.

Some limitations of this study need to be highlighted as a basis for future research. Firstly, we used the number of reviews as a proxy to measure actual hotel sales. Although this has been shown to be a valid approach in previous research, it may cause an information distortion which could influence the results. This approach should therefore be retested in future studies. Secondly, we used a positive/negative analysis to capture customer ratings of their hotel stay. More advanced methods could be applied to reflect the complex expression of customer opinion more comprehensively.

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