Proceedings of the 54th Hawaii International Conference on System Sciences | 2021

Understanding the "Holiday Effect" in Online Restaurant Ratings

Lingfei Deng
Harbin Institute of Technology
denglingfei@hit.edu.cn

Dapeng Xu
Harbin Institute of Technology
dpxu@hit.edu.cn

Qiang Ye
Harbin Institute of Technology
yeqiang@hit.edu.cn

Abstract

Plenty of studies have demonstrated the holiday effect in human decision-makings. However, extant research fails to explore whether and how a holiday effect exists in online word-of-mouth generation. This work utilizes online restaurant reviews obtained from the most popular review platform in China to investigate this question with multiple empirical tests. The results suggest that diners are more likely to give a lower online rating on holidays, and this relationship is driven by a combination of restaurants' specific reasons and diners' specific factors. Specifically, the level of crowdedness and the quality of the restaurant can partly explain this relationship. Moreover, reviewers are found to be driven by cognitive mental processes instead of being carried away by emotions when they post online ratings on holidays. However, those who need to work overtime during holidays are found to be driven by bad mood when they post online ratings.

1. Introduction

In modern digital economy, sellers and buyers are able to make transactions online thanks to the rapid development of the Internet and IT infrastructure [1]. They do this on e-marketplace platforms, which plays an increasingly important role in individuals' consumption behaviors [2] Consumers can share their opinions on a product or service on review platforms [3]. Previous studies demonstrate that consumers are willing to express their emotions (e.g. sadness, anger, anxiety, joy, happiness, etc.) through online reviews [4]. Online reviews have been demonstrated to have a significant influence on firms' reputation and sales performance [5]. Online ratings are the most common function on review platforms, which enable consumers to express their attitudes (positive or negative) toward the products or services with an evaluation score. Higher online ratings indicate the more positive attitudes of the reviewers. Thus, rating competition in e-marketplace is similar to advertising competition in traditional markets. Online review ratings indicate sellers' reputation, which in turn can influence consumers' purchase frequency and sales performance [6,7].

Given the importance of online review ratings, existing studies have explored a lot about the antecedents of online ratings. Bakhshi et al. (2014) have explored the impacts of price range, restaurant features, service, and advertisement of the restaurants on online review ratings [8]. Byers et al. (2012) find that online promotions can affect the subsequent online review ratings [9]. In addition, management response is demonstrated to influence a firm's goodwill (online ratings) [5]. Reviewers' demographics are also found to be important factors for online review ratings, e.g., income, education level, and diversity index of residents [8]. Hong et al. (2018) also find that travelling consumers are more likely to post higher online ratings [10].

However, existing studies rarely touch the impacts of holidays on online review behavior, which has already been investigated in some studies on offline consumer behavior, particularly in restaurant service [11]. On holidays, consumers are more likely to conduct social activities, especially food-related activities to make family, lover and friend reunions [11], and express their consumption satisfaction [12]. However, in the field of online word-of-mouth, some studies investigating online reviews merely consider holiday as a control variable rather than a main effect [13,14]. For example, Lu et al. (2013) use holiday as a control variable when studying the promotional marketing and online word-of-mouth of restaurants [13]. Existing literature has not answered the question whether and how holiday, as the main effect, will affect online review ratings.

To fill this research gap, our study tries to address two main questions in restaurant service evaluation: (1) Will diners be influenced by holidays when they eat out and post online review ratings? (2) And if so, what drives the holiday effect in online ratings?

URI: https://hdl.handle.net/10125/71125
978-0-9981331-4-0

The remainder of this paper is structured as follows. Section 2 introduces the concept of online rating behavior and posits hypothesis based on a literature review. Research methodology, including data collection, variable descriptions, and model development, is stated in Section 3. Section 4 shows the results of descriptive analysis, main empirical analysis, and the robustness check. Section 5 explores the drivers underlying the relationship between holiday and online ratings. Finally, we discuss and conclude our work in Sections 6 and 7.

2. Theoretical background and hypothesis

2.1. Online rating behavior

As a prominent form of online word-of-mouth, online reviews are playing a more and more important role in electronic markets. Many review platforms provide registered users with a rating function to post their attitude and satisfaction toward the products or services [15]. Online review ratings reflect a reviewer's evaluation score for a product or service based on his/her personal consumption experiences [3]. In theory, the higher the online ratings, the more positive and satisfied the consumers are toward the products or services [13]. Online review ratings is analogous to an advertising that reflects a merchant's goodwill, which can affect consumers' purchase decisions [16] and in turn the sales performance [6].

2.2. How holidays affect online ratings?

Prior literature has studied the holiday effect in various fields, especially the stock market [17,18], marketing (e.g. consumer behavior) [19,20], tourism [21], etc. Most of these studies find a positive holiday effect, indicating that individuals are more likely to be in a good mood on holidays [22]. However, negative mood has also be found to be associated with the holiday effect, indicating that individuals might also experience unpleasant feelings on holidays [21]. For example, Coakley et al. (2008) find that the Mid-Autumn Festival is negatively related to investors' sentiment, and thus negatively affects the stock market [23]. We argue that a negative effect exists in the relationship between holiday and online ratings based on the logic as below.

Holiday enables people to escape from busy life by pursuing social activities and food-related activities. This tends to lead to crowded environment. People are more likely to crowd into stores, restaurants and other different places to enhance relationships with family, lover and friends [24,25]. We assume that people will conduct more social interactions on holidays than on non-holidays. Social transmission and social sharing drive individuals to share their experiences, such as by expressing their feelings about their social activities in online reviews [26].

This promotes consumption on holidays. Dining places such as restaurants are good places for people to make reunions [27], making them good candidates for over crowdedness on holidays. Psychological research has demonstrated the relationship between consumers' negative mood and crowded service environment [28]. Diners have strong demands for service quality, food quality, waiting time, dining environment, and price, etc. [29]. However, crowded dining venues on holidays usually exceed diners' tolerance level of crowd [30], and can also lead to long waiting time, low service and food quality. Therefore, such restaurant experiences on holidays tend to lead to bad mood in consumers, and then affect their satisfaction [31,32] and evaluation [33]. These findings reverberate well with the psychological research results showing that mood can influence human judgment and behavior [34].

Online ratings are a good way for diners to express their dining experience. Extant studies have revealed that the accumulated prior reviews can be observed a downward trend for ratings because of later consumers' decreased enthusiasm [35]. However, in the context of online restaurant reviews, rating increase has also been documented and can be explained by popularity influence [36]. Therefore, we can explore holiday effect in online restaurant ratings without considering the selection bias of consumers' rating decrease. What's more, in the context of online restaurant reviews, reviewers tend to be positive on posting online ratings, which has been observed a higher rating than neutral ones (e.g., higher than 3-star or even 4-star in the five-star ratings system) [35-38]. Thus, we can observe holiday effect without considering the negative bias in our study. We assume that after diners had unpleasant restaurant experience on holidays, they tend to post negative reviews on review platforms [4]. Thus, we posit our hypothesis as below.

Holiday has a negative effect on online ratings, i.e., a diner eating out on holidays is more likely to post a review with a lower rating.

3. Research methodology

3.1. Data collection

We obtained our main dataset from Dianping (Dianping.com). Dianping is the most popular and widely used consumer reviews platform in China, which is a review platform offering detailed information of numerous businesses (e.g. restaurants, hotels, entertainments, tours, etc.) across the cities in China and some other hot tourist countries. The most popular business that receives the most attention and provides the most information on Dianping is the catering business (mainly restaurant service). Nowadays, consumers are willing to spend a considerable amount of time on Dianping searching for information and making comparison for the restaurant services to make the right decision when they decide to dine out[13,15]. It is worth noting that any registered users on this platform can express their satisfaction about the restaurant service by posting reviews, including review text, review ratings (ranging from one star to five stars), the average price per person for their dining, and also the ratings of service quality, environment, and taste of food. The review information of the restaurants is analogous to traditional advertising, which can affect the reputation (goodwill) of the restaurants and capture consumers' awareness.

To test the research model, we collected review information, restaurant-related and reviewer-related information of top ten popular restaurants (identified by the review volume) on Dianping from 15 randomly selected major cities (i.e., Changchun, Changsha, Chengdu, Chongqing, Dalian, Guiyang, Harbin, Jinan, Lhasa, Nanchang, Nanning, Sanya, Xiamen, Yinchuan, and Zhengzhou) in China for the period from December 2013 to November 2017. We also obtained other restaurant-related information like review volume and location, and reviewer-related information like review date, registration date, followers, historical reviews, contribution, the per person price given to a restaurant, etc.

As prior literature demonstrates that more than 75 percent of reviewers post their reviews during or immediately after their dining time on Dianping [38]. Therefore, we can investigate the relationship between holidays and online ratings based on the assumption that reviewers tend to be affected by the holiday effect on the day they experiencing the restaurants. We got a final sample that consists of 324,783 reviews in total.

3.2. Variables

3.2.1. Dependent variable. The online rating function on Dianping is based on a five-star system (from 1 to 5), which is also an indicator of online consumers' satisfaction with their consumption experiences. The higher online ratings given by a diner to a restaurant, the more satisfied with the restaurant services [13]. Thus, we use the online ratings of the restaurant service as dependent variable to study holiday effect on diners' online rating behavior.

3.2.2. Independent variable. Holiday is defined as a dummy variable, which is equal to 1 if a diner posts his/her review on holidays, and 0 otherwise. We assume that when a diner posts his/her review for a restaurant service on Dianping, he/she is affected by the consumption experiences during the day he/she dines out in this restaurant. That is, we use the review date as the dining out date to distinguish holidays and non-holidays [8]. More importantly, Chinese people nowadays prefer to dine out (joining in some eating activities) on holidays to make family, lovers and friends reunions [11,39]. The holidays (31 in total) we consider in this study include Chinese statutory holidays, some other Chinese lunar calendar holidays, some other international and western holidays, and some modern holidays created or expanded by Chinese.

3.2.3. Control variables. We added some reviewer-related and restaurant-related variables, which may also affect online ratings to rule out other possible alternative explanations, as control variables.

Reviewer-related variables include *Gender*, which is a dummy variable that is equal to 1 if a reviewer is a female diner, and 0 otherwise [12,40]. As Dianping provides the location information of both the reviewed restaurant and the reviewer, we can identify whether a reviewer is a native or a tourist by comparing his/her residence with the location of the reviewed restaurant. Thus, *Native* is a dummy variable that is equal to 1 if a reviewer is a native (the location of the restaurant is the same as the reviewer's residence) and 0 if a reviewer is a tourist [10]. *Followers*, measured as the number of fans following a reviewer (Dianping allows a registered user to follow other users), and natural logarithmic transformed; *Registration*, measured as the number of days from the day a reviewer registered on Dianping to the day he/she posted a review, and natural logarithmic transformed; *Expertise* is defined as a reviewer's level of expertise, which is calculated according to the contribution and the historical number of reviews a reviewer previously published [15]. That is, Expertise=0.5 × Log (the contribution of a reviewer+1) + 0.5 × Log (the historical number of reviews the reviewer previously published+1); *Travel* denotes a reviewer's travelling experience, measured as the number of cities he/she has previously traveled to, and natural logarithmic transformed.

Restaurant-related variables include *Price*, measured as the mean price per person that is given by all the reviewers for a restaurant, and natural logarithmic transformed; *Popularity*, measured as the review volume of a restaurant, and natural logarithmic transformed; *City*, a dummy variable that measured as the city that a restaurant locates in to control the fixed effect of location.

For all of the natural logarithmic transformed variables, we add 1 before taking the natural log considering the raw values that equal to zero [41].

3.3. Model development

We use the following linear regression model to examine the relationship between holidays and ratings:

$$\begin{aligned} Rating = {} & \beta_0 + \beta_1 Holiday + \beta_2 Gender + \beta_3 Native \\ & + \beta_4 Followers + \beta_5 Registration + \beta_6 Expertise \\ & + \beta_7 Travel + \beta_8 Price + \beta_9 Popularity + \beta_{10} City + \varepsilon \end{aligned} \quad (1)$$

The upper bound of online review ratings on Dianping is 5 stars. This platform uses a 5-star ratings scheme for reviewers to post their opinions. Online consumers indicate their satisfaction with their consumption experiences using this system, which is similar to other review platforms. A higher online rating indicates a consumer's higher satisfaction with the restaurant services [13]. Thus, we use the rating of the restaurant service (*Rating*) as the dependent variable to study the holiday effect in diners' online rating behavior.

Table 1. Descriptive statistics and correlation coefficient of all variables

Variable	1	2	3	4	5	6	7	8	9	10
1. Rating	1									
2. Holiday	-0.018*	1								
3. Gender	0.011*	-0.012*	1							
4. Native	-0.004	-0.033*	0.036*	1						
5. Followers	-0.063*	-0.002	-0.012*	-0.104*	1					
6. Registration	-0.014*	0.017*	0.059*	-0.211*	0.180*	1				
7. Expertise	-0.172*	-0.012*	0.153*	-0.045*	0.539*	0.303*	1			
8. Travel	-0.153*	0.010*	0.033*	-0.391*	0.438*	0.293*	0.724*	1		
9. Price	0.045*	0.006*	-0.019*	-0.086*	-0.010*	0.093*	-0.073*	-0.002	1	
10. Popularity	0.055*	-0.002	0.022*	-0.050*	-0.005*	0.104*	-0.052*	-0.053*	0.245*	1
Mean	4.375	0.155	0.719	0.452	2.718	6.675	4.276	1.253	4.379	8.665
S.D.	0.921	0.361	0.450	0.498	1.410	1.100	1.395	0.893	0.405	0.577
VIF		1.00	1.05	1.43	1.44	1.18	3.04	2.94	1.08	1.08

Note: *: Correlation is significant at the 0.01 level.

4. Results

4.1. Descriptive analysis

The descriptive statistics and pairwise correlations of all variables are shown in Table 1. The average review rating of selected restaurants is 4.375, which is a high value regarded as positive ratings on Dianping. 15.5% of diners post their reviews on holidays, 71.9% of the reviewers are women, and 45.2% of the reviewers are natives.

We also checked multicollinearity by calculating pairwise correlation coefficients and Variance Inflation Factor (VIF) values of main variables. As we can see in Table 1, the mean value of VIF is 1.58 with the highest value of 3.04, which is far below the threshold value of 10 [42] and suggests no major multicollinearity concerns in this study.

4.2. Main analysis

We examine the impact of *Holiday* on online ratings using a linear regression model. Table 2 reports the results. First, we only added the control variables to the model (Model 1). The results show that all the control variables can significantly affect online ratings. A more popular restaurant (received more reviews) is more likely to receive negative reviews (low online ratings). A reviewer who is a female, has more followers and has registered earlier on Dianping is inclined to give high ratings. In addition, a higher priced restaurant is more likely to receive positive reviews (high online ratings). A reviewer who is a native, with higher level of review expertise and travel experience is found to contribute more to lower online ratings. All the results are in line with our expectations, which indicating that we can continue to use the econometric model we constructed to test our hypothesis.

Second, we added the independent variable into the model (Model 2) to test our hypothesis, which predicts negative relationship between *Holiday* and *Rating*. As we can see in Model 2, the impact of *Holiday* on online ratings is negatively significant (β=-0.051, p<0.01). Thus, our hypothesis is supported, indicating that diners are more likely to give lower ratings on holidays when they eating out in restaurants.

The R^2 in Model 1 to Model 2 are 0.049 and 0.050, respectively, which indicating that adding the independent variable (*Holiday)* can improve the explanatory power of the model.

Table 2. Holiday effect in online ratings

Variable	*Rating*	
	Model 1	Model 2
Gender	0.071***	0.071***
	(0.004)	(0.004)
Native	-0.052***	-0.054***
	(0.004)	(0.004)
Followers	0.028***	0.028***
	(0.001)	(0.001)
Registration	0.027***	0.027***
	(0.002)	(0.002)
Expertise	-0.102***	-0.102***
	(0.002)	(0.002)
Travel	-0.073***	-0.072***
	(0.003)	(0.003)
Price	0.073***	0.074***
	(0.004)	(0.004)
Popularity	-0.026***	-0.026***
	(0.006)	(0.006)
Holiday		-0.051***
		(0.005)
City	Included	Included
Constant	4.596***	4.604***
	(0.052)	(0.052)
Obs#	324,777	324,777
R^2	0.049	0.050

Notes: Robust standard errors are included in parentheses.
***: p<0.01.

4.3. Within-reviewer robust check

We further conduct a within-reviewer analysis [26,35] to explore whether review ratings are influenced by holidays by considering diner characteristics that may systematically influence their online rating behavior.

Table 3. Holiday effect in the within-reviewer ratings

Variable	*Rating*	
	Model 1	Model 2
Price	0.080***	0.080***
	(0.013)	(0.013)
Popularity	0.030***	0.030***
	(0.004)	(0.004)
Holiday		-0.024**
		(0.012)
City	Included	Included
Constant	3.564***	3.568***
	(0.104)	(0.105)
Obs#	50,459	50,459
R^2	0.026	0.026
Number of users	1,115	1,115
Reviewer Fixed Effect	YES	YES

Notes: Robust standard errors are included in parentheses.
**: p<0.05; ***: p<0.01.

We randomly select 1,600 reviewers from the initial sample who had contributed more than one reviews on both holidays and non-holidays. Then, we collect related data at a reviewer-level, namely, every historical review of restaurants written by these reviewers on Dianping, including data on the restaurants and reviewers. The research period is the same as in our main analysis, i.e., December 2013 to November 2017. The resulting subsample consists of 50,459 reviews by 1,115 reviewers. We create a reviewer-level panel to control for reviewer fixed effects to examine whether the holiday effect is still present in the within-reviewer online ratings.

Table 3 reports the results of the within-reviewer analysis. As we can see in Model 2, the coefficient of *Holiday* is significantly negative (β=-0.024, p<0.05), suggesting that diners are more likely to post lower online ratings of restaurants on holidays. These results demonstrate the robustness of the findings in the main analysis.

5. What drives holiday effect in online ratings?

The decrease in online ratings on holidays can be explained either by restaurants' specific reasons or diners' specific factors, or by a combination of both. To determine the underlying mechanisms of negative online ratings on holidays, we conduct a series of analyses at restaurant-level and reviewer-level, respectively.

5.1. Restaurant-level analysis

5.1.1. More crowded, more negative? As proposed in section 2.2, crowded dining venues on holidays usually exceed diners' tolerance level of crowd [30], and lead to bad mood in consumers, and then affect consumers' satisfaction [31,32] and lead to negative online rating behavior [33]. Thus, we assume that a reviewer experiencing more crowded restaurant on holidays is more negative to their dining experiences and tend to post more negative online ratings. That is, crowdedness is one of the drivers of the negative holiday effect in online ratings. We measure the level of crowdedness as the percentage of reviews on holidays to the overall historical reviews of each restaurant, and divide the restaurants into high crowded and low crowded groups based on the median. Then, we develop two linear regression models for the high crowded and low crowded groups, respectively, and use SU-test based on SUR estimation to test the coefficient differences of *Holiday* in these two groups.

The results are shown in Table 4. The coefficient of *Holiday* in high crowded group (β=-0.062, p<0.01) is more negative than that in low crowded group (β=-0.041, p<0.01), showing that reviewers experiencing a more crowded restaurant on holidays is more likely to post negative reviews, thus strengthen the negative impact of *Holiday* on online ratings. The difference in coefficient estimates of *Holiday* between two groups is

-0.021 with the *P*-value lower than 0.01 significance level, demonstrating the significant moderating effect of crowdedness once more.

5.1.2. Lower quality, more negative? In order to investigate whether quality of restaurants has influence on the decrease in online ratings on holidays, we conduct comparisons between high-quality and low-quality restaurants. Specifically, we divide the restaurants into high service quality and low service quality groups, high environment quality and low environment quality groups, high taste quality and low taste quality groups based on the median of multidimensional ratings of service, environment, and taste of each restaurant. Then, we develop linear regression models respectively, and use SU-test based on SUR estimation to test the coefficient differences of *Holiday* in these groups.

The results are shown in Table 4. The coefficient of *Holiday* in low service quality group (β=-0.070, p<0.01) is more negative than that in high service quality group (β=-0.032, p<0.01), in low environment quality group (β=-0.059, p<0.01) is more negative than that in high environment quality group (β=-0.042, p<0.01), in low taste quality group (β=-0.071, p<0.01) is more negative than that in high taste quality group (β=-0.033, p<0.01), showing that reviewers experiencing a lower quality restaurant on holidays is more likely to post negative reviews, thus strengthen the negative impact of *Holiday* on online ratings. The difference in coefficient estimates of *Holiday* between each two groups is 0.038, 0.017, and 0.038 with the *P*-value lower than 0.01, 0.10, and 0.01 significance level, respectively, demonstrating the significant moderating effect of restaurant quality once more.

Table 4. Restaurant-level subsample analyses

Variable	*Rating*							
	High Crowded	Low Crowded	High Service	Low Service	High Environment	Low Environment	High Taste	Low Taste
Gender	0.063***	0.083***	0.063***	0.074***	0.054***	0.084***	0.062***	0.078***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Native	-0.008	-0.068***	-0.057***	-0.031***	-0.040***	-0.027***	-0.051***	0.001
	(0.006)	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.006)	(0.007)
Followers	0.026***	0.028***	0.026***	0.024***	0.026***	0.027***	0.028***	0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Registration	0.022***	0.028***	0.029***	0.011***	0.029***	0.012***	0.028***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Expertise	-0.085***	-0.117***	-0.113***	-0.076***	-0.107***	-0.086***	-0.111***	-0.077***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Travel	-0.072***	-0.067***	-0.053***	-0.092***	-0.056***	-0.093***	-0.057***	-0.089***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Price	0.070***	0.027***	0.073***	0.011**	-0.016*	0.004	0.121***	0.025***
	(0.006)	(0.008)	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)
Popularity	-0.017	-0.029***	-0.038***	-0.079***	-0.027***	-0.079***	-0.019**	-0.095***
	(0.012)	(0.008)	(0.009)	(0.011)	(0.009)	(0.009)	(0.008)	(0.012)
Holiday	-0.062***	-0.041***	-0.032***	-0.070***	-0.042***	-0.059***	-0.033***	-0.071***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
City	Included	Included	Included	Included	Included	Included	Included	Included
Constant	4.433***	4.903***	4.777***	5.106***	5.054***	5.176***	4.436***	5.168***
	(0.088)	(0.074)	(0.077)	(0.087)	(0.084)	(0.077)	(0.077)	(0.091)
Obs#	161,182	163,595	161,219	163,558	160,627	164,150	162,031	162,746
R^2	0.053	0.063	0.045	0.033	0.050	0.044	0.046	0.035

Notes: Robust standard errors are included in parentheses.
* p < 0.1, ** p < 0.05, *** p < 0.01

5.2. Reviewer-level analysis

5.2.1. Rational or carried away by emotions? We draw on mental processes theory to explore whether the reviewers' negative holiday online rating behavior is driven by perceptive, affective, or cognitive mental processes.

Perceptive mental processes are the percept-based processing that reflect individuals' processes of seeing and hearing, which is rarely considered when investigating mental process effects in prior studies about online reviews. Whereas, affect-based and cognition-based processing have been a hot topic with great debate in the field of physiological, psychology, and online reviews. Affect-based processing incorporates processes of feeling, liking, and emotions related to the issue or object being evaluated and predicted, which is considered emotional processes; whereas cognition-based processing incorporates processes of thinking, knowing, and understanding associated with the issue or object, which is considered rational and logical processes. These mental processes then further influence peoples' judgements and evaluations [43,44]. Physiological studies [45,46] show that if people' affective mental processes dominate when they conduct information processing, they will be less likely to draw on cognition-based processing, and vice versa. For example, Huang, Hong, and Burtch (2016) demonstrated that affect (emotion) and cognition (reason) come into conflict in judgement and decision-making by examining consumers' online review behavior [47]. If consumers draw on affect-based processing when they write online reviews, they will be more likely to express affective words (e.g. anxious, anger, sad, happy). Correspondingly, if consumers draw on cognition-based processing when they write online reviews, they will be more likely to express cognitive words (e.g. insight, cause, and certain words). We summarize that consumers will draw on one type of mental process at the expense of other processes when they craft online reviews.

In addition, according to human cognitive load theory, individuals can face cognitive limitation when they need to cope with multiple tasks [48]. In the context of our study, consumers' brain will not have to be dominated by tedious work and under cognitive load when they write online reviews on holidays, and then they can rely on cognition-based processing during holidays. Thus, we expect that consumers may express less work-related words when crafting online reviews on holidays.

Table 5. Mental processes influence

Variable	*Work*	*Affective*	*Perceptive*	*Cognitive*
	Model 1	Model 2	Model 3	Model 4
Gender	-0.023***	0.007*	0.062***	0.030***
	(0.004)	(0.004)	(0.004)	(0.003)
Native	0.005	0.024***	-0.152***	0.061***
	(0.005)	(0.005)	(0.005)	(0.004)
Followers	0.018***	0.012***	-0.002	-0.001
	(0.001)	(0.002)	(0.002)	(0.001)
Registration	0.011***	-0.010***	0.010***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.001)
Expertise	-0.029***	-0.043***	-0.012***	0.075***
	(0.002)	(0.002)	(0.002)	(0.002)
Travel	0.006*	0.000	0.025***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Price	0.248***	0.157***	-0.107***	-0.036***
	(0.004)	(0.005)	(0.005)	(0.004)
Popularity	-0.066***	-0.001	-0.106***	0.029***
	(0.007)	(0.007)	(0.007)	(0.005)
Holiday	-0.015***	-0.019***	-0.021***	0.014***
	(0.005)	(0.005)	(0.005)	(0.004)
City	Included	Included	Included	Included
Constant	0.303***	1.084***	2.800***	2.595***
	(0.054)	(0.059)	(0.056)	(0.044)
Obs#	324,777	324,777	324,777	324,777
R^2	0.024	0.010	0.012	0.019

Notes: Robust standard errors are included in parentheses.
*: p<0.1; ***: p<0.01.

Following prior research [41,49], we use a text-mining tool to extract content associated with the related words that are embedded in the reviews. Specifically, we use TextMind, which is a Chinese language psychological analysis system that analyzes the linguistic characteristics of a given Chinese text [50]. Before analyzing the linguistic characteristics, we first use Python to clean and remove the special characters in the review text. Using TextMind, we use *Work* as a proxy variable to indicate reviewers' work concerns on holidays and measure *Work* as the percentage of work-related words in a given review text. The significantly negative coefficient of *Holiday* on *Work* (β=-0.015, p<0.01) in Model 1 in Table 5 suggests that reviewers do escape from their busy work and have more time to encounter and recall holiday experiences, as reviewers express less related to work when writing reviews. Thus, reviewers are more likely to rely on cognition-based processing on holidays.

Furthermore, we examine which type of mental processes take hold on reviewers' holiday rating behavior. We assume that cognitive mental processes may dominate rather than affective (or perceptive) mental processes, as consumers will not have to be under cognitive load on holidays and they can rely on central cognitive analysis, although unhappy experiences may lead to more affect-based processing. Again, using TextMind, we use *Affective*, *Perceptive*, and *Cognitive* as proxy variables to indicate reviewers' affect, percept, and cognition-based processing on holidays and measure *Affective*, *Perceptive*, and *Cognitive* as the percentage of each type of mental processes related words in each review text. Models 2 to 4 in Table 5 report the results of reviewers' mental processes on holidays when they conduct evaluation and write reviews. We observe that on holidays, the use of cognition-based processing words increases (β=0.014, p<0.01), while the use of affect and percept-based processing words decreases (β=-0.019, p<0.01; β=-0.021, p<0.01, respectively), which demonstrates that consumers do draw on cognitive mental processes on holidays. Consumers are logical and rational when they crafting online reviews on holidays instead of being carried away by emotions.

5.2.2. Busier work, more negative? As mentioned in section 5.2.1, individuals who have to cope with tedious work and multiple tasks can face cognitive limitation, and they are more likely to rely on affect-based processing. Thus, we assume that consumers who need to work overtime during holidays are more likely to have bad mood, and then tend to give lower online ratings toward the restaurants. We divide the reviewers into good mood and bad mood groups based on the median of *Work* expression of each reviewer. Then, we develop two linear regression models for these two groups, respectively, and use SU-test based on SUR estimation to test the coefficient differences of *Holiday*.

The results are shown in Table 6. The coefficient of *Holiday* in bad mood group (β=-0.074, p<0.01) is more negative than that in good mood group (β=-0.028, p<0.01), showing that reviewers experiencing more tedious work and have worse mood on holidays are more likely to post negative reviews, thus strengthen the negative impact of *Holiday* on online ratings. The difference in coefficient estimates of *Holiday* between these two groups is -0.046 with the *P*-value lower than 0.01 significance level, demonstrating the significant moderating effect of reviewers' mood once more.

Table 6. Mood influence

Variable	*Rating*	
	Bad mood	Good mood
Gender	0.063***	0.079***
	(0.006)	(0.005)
Native	-0.059***	-0.049***
	(0.006)	(0.006)
Followers	0.033***	0.025***
	(0.002)	(0.002)
Registration	0.023***	0.030***
	(0.002)	(0.002)
Expertise	-0.098***	-0.102***
	(0.003)	(0.003)
Travel	-0.079***	-0.064***
	(0.004)	(0.004)
Price	0.095***	0.063***
	(0.007)	(0.006)
Popularity	-0.025***	-0.028***
	(0.010)	(0.009)
Holiday	-0.074***	-0.028***
	(0.007)	(0.006)
City	Included	Included
Constant	4.453***	4.688***
	(0.078)	(0.068)
Obs#	162,363	162,414
R^2	0.059	0.041

Notes: Robust standard errors are included in parentheses.
***: p<0.01.

6. Conclusion

Extant studies rarely explore the impact of holidays on consumers' online review behavior. Little research uses psychological theories with holiday effect in the field of online reviews. This study uses the data collected from the most review platform to examine diners' online rating behavior by taking the holiday effect into consideration. The results show that the holiday effect does exist in diners' online rating behavior. To be more specific, diners are more likely to generate more negative online ratings during holidays. We also try to explore the potential mechanisms underlying the relationship between holidays and online ratings. We find that the level of crowdedness and the quality of the restaurant can drive the negative holiday effect in online ratings. Moreover, reviewers' more negative online rating behavior on holidays is under their cognitive mental processes, suggesting that reviewers are rational rather than carried away by emotions when they post online ratings on holidays. However, those reviewers who suffer tedious work during holidays can be emotional and give lower online ratings due to their bad mood. Finally, we believe that we have made meaningful contributions to both practice and theory in the field of online WOM, and expect more detailed and comprehensive future work.

7. Discussions

7.1. Theoretical implications

Our study contributes to the online rating and even the online review literature by introducing the holiday effect. Our work has multiple advancements.

First, we extend the online rating literature by investigating the holiday effect in online ratings. The extant literature rarely examines the impact of holiday effect in online ratings, with just a few studies merely studying the control effect of holiday. Our study considers holiday as a main effect and shows that holiday effect exists in reviewers' online rating behavior, and particularly has a negative effect on online ratings in restaurant service. Consumers are more likely to conduct eating activities on these holidays [11].

Second, our research takes an initial attempt to comprehensively examine the holiday effect with considering the restaurant-level factors. The findings reveal that the level of crowdedness and the quality (i.e., the quality of service, environment, and taste) of the restaurants are the drivers underlying the relationship between holidays and online ratings.

Third, our study considers a novel aspect of reviews: reviewer-level specific factors. We provide the first theoretical explanation of how the negative relationship between holidays and online ratings is driven by reviewers' cognitive mental processes. We find that reviewers are rational when they crafting online reviews, instead of being carried away by emotions as previous thought. However, we also find that reviewers who suffer tedious work during holidays are tend to be affected by bad mood when giving online ratings.

7.2. Practical implications

Our empirical results yield important practical implications for restaurant service. First, holiday is demonstrated to have a negative effect on online ratings. A possible explanation for this result is that eating places are commonly crowded on holidays, and this leads to long waiting time, low services, and food quality. Such restaurant experiences on holidays may lead to bad mood in consumers, and then affect consumer satisfaction [31,32]. Managers in restaurant service should pay more attention to their service quality and food quality on holidays, and employ strategies to moderate diners' bad mood.

Second, our findings suggest that reviewers' online rating behavior rely on their cognitive mental processes. When crafting online reviews and posting online ratings, reviewers are rational and logical rather than emotional. As Nahl and Tenopir (1996) show that cognition domain incorporate understanding the concepts of an issue or project [51], whenever possible, restaurant managers should develop strategies to help diners have a deep understanding of their dishes, promotions, environment, and services to alleviate diners' unhappiness and dissatisfactions on holidays. What's more, restaurant managers also need to pay attention to those who perform bad mood (e.g., due to tedious work) when experiencing meals, as these people tend to be driven by their bad mood when posting online ratings.

7.3. Limitations and future research

As with any other study, our study has some notable limitations. First, we only collect review data from restaurant industry, and confirm the impact of holidays on dining experience and online ratings. Future work can extend this study to other domains such as hospitality industry. Second, we merely observe the contemporaneous effect of holiday effect. We will consider the pre-holiday effect and post-holiday effect in our future work. Third, we plan to use text-mining techniques to test the specific mental processes. We will develop a deeper understanding of reviewers' online rating behavior by investigating the effects of specific cognitive mental processes, such as insight, cause, and certain processes, etc. and specific affective mental processes, such as negative emotions, positive emotions, anxious, happy, hurtful, ugly, and nasty processes, etc.

8. Acknowledgements

The authors would like to thank the editor and reviewers for their helpful and constructive suggestions. This work was supported by the National Natural Science Foundation of China [Grant # 71532004, 71801063, and 71850013] and the China Postdoctoral Science Foundation [Grant # 2018M640300].

9. References

[1] C. Avery, P. Resnich, R. Zeckhauser. 1999. The market for evaluations, American Economic Review, 89(3), pp. 564-584.

[2] T. Eisenmann, G. Parker, M. Van Alstyne. 2011. Platform envelopment, Strategic Management Journal, 32(12), pp. 1270-1285.

[3] Y. Chen, J. Xie. 2008. Online consumer review: Word-of-mouth as a new element of marketing communication mix, Management Science, 54(3), pp. 477-491.

[4] P.U. Nyer. 1997. A study of the relationships between cognitive appraisals and consumption emotions, Journal of the Academy of Marketing Science, 25(4), pp. 296-304.

[5] W. Chen, B. Gu, Q. Ye, K.X. Zhu. 2019. Measuring and managing the externality of managerial responses to online customer reviews, Information Systems Research, 30(1), pp. 81-96.

[6] J.A. Chevalier, D. Mayzlin. 2006. The effect of word of mouth on sales: Online book reviews, Journal of Marketing Research, 43(3), pp. 345-354.

[7] Y. Liu. 2006. Word of mouth for movies: Its dynamics and impact on box office revenue, Journal of Marketing, 70(3), pp. 74-89.

[8] S. Bakhshi, P. Kanuparthy, E. Gilbert. 2014. Demographics, weather and online reviews: A study of restaurant recommendations, in WWW '14 Proceedings of the 23rd International Conference on World Wide Web. Seoul, Korea.

[9] J.W. Byers, M. Mitzenmacher, G. Zervas. 2012. The groupon effect on yelp ratings: A root cause analysis, in Proceedings of the 13th ACM Conference on Electronic Commerce.

[10] H. Hong, Q. Ye, D. Xu, Y. Jin. 2018. Travel and online review behavior, in Proceedings of the 22nd Pacific Asia Conference on Information Systems (PACIS). Yokohama, Japan.

[11] A. Khare, J.J. Inman. 2009. Daily, week-part, and holiday patterns in consumers' caloric intake, Journal of Public Policy & Marketing, 28(2), pp. 234-252.

[12] M. Kozak. 2010. Holiday taking decisions – the role of spouses, Tourism Management, 31(4), pp. 489-494.

[13] X. Lu, S. Ba, L. Huang, Y. Feng. 2013. Promotional marketing or word-of-mouth? Evidence from online restaurant reviews, Information Systems Research, 24(3), pp. 596-612.

[14] T. Song, J. Huang, Y. Tan, Y. Yu. 2019. Using user- and marketer-generated content for box office revenue prediction: Differences between microblogging and third-party platforms, Information Systems Research, 30(1), pp. 191-203.

[15] Y.-H. Cheng, H.-Y. Ho. 2015. Social influence's impact on reader perceptions of online reviews, Journal of Business Research, 68(4), pp. 883-887.

[16] W. Jabr, Z.E. Zheng. 2014. Know yourself and know your enemy: An analysis of firm recommendations and consumer reviews in a competitive environment, MIS Quarterly, 38(3), pp. 635-654.

[17] D. Garcia. 2013. Sentiment during recessions, The Journal of Finance, 68(3), pp. 1267-1300.

[18] V.V. Acharya, O. Merrouche. 2013. Precautionary hoarding of liquidity and interbank markets: Evidence from the subprime crisis, Review of Finance, 17(1), pp. 107-160.
[19] Z. Cao, K.-L. Hui, H. Xu. 2018. When discounts hurt sales: The case of daily-deal markets, Information Systems Research, 29(3), pp. 567-591.
[20] Y. Lu, A. Musalem, M. Olivares, A. Schilkrut. 2013. Measuring the effect of queues on customer purchases, Management Science, 59(8), pp. 1743-1763.
[21] J. Nawijn, M.A. Marchand, R. Veenhoven, A.J. Vingerhoets. 2010. Vacationers happier, but most not happier after a holiday, Applied Research in Quality of Life, 5(1), pp. 35-47.
[22] R. Chong, R. Hudson, K. Keasey, K. Littler. 2005. Pre-holiday effects: International evidence on the decline and reversal of a stock market anomaly, Journal of International Money and Finance, 24(8), pp. 1226-1236.
[23] J. Coakley, J.M. Kuo, A. Wood. 2008. Negative sentiment and the lunar moon festival effect, in the 2008 EFMA Meeting. Athens, Greece.
[24] C. Dellarocas, G. Gao, R. Narayan. 2014. Are consumers more likely to contribute online reviews for hit or niche products? Journal of Management Information Systems, 27(2), pp. 127-158.
[25] B. Du, W. Zhou, C. Liu, Y. Cui, H. Xiong. 2019. Transit pattern detection using tensor factorization, INFORMS Journal on Computing, 31(2), pp. 193-206.
[26] N. Huang, Y. Hong, G. Burtch. 2016. Social network integration and user content generation: Evidence from natural experiments, MIS Quarterly, 41(4), pp. 1035-1058.
[27] B. Heimtun. 2010. The holiday meal: Eating out alone and mobile emotional geographies, Leisure Studies, 29(2), pp. 175-192.
[28] S. Wei, T. Ang, N.A. Anaza. 2019. The power of information on customers' social withdrawal and citizenship behavior in a crowded service environment, Journal of Service Management, 30(1), pp. 23-47.
[29] B. Sparks, J. Bowen, S. Klag. 2003. Restaurants and the tourist market, International Journal of Contemporary Hospitality Management, 15(1), pp. 6-13.
[30] K.A. Machleit, J.J. Kellaris, S.A. Eroglu. 1994. Human versus spatial dimensions of crowding perceptions in retail environments: A note on their measurement and effect on shopper satisfaction, Marketing Letters, 5(2), pp. 183-194.
[31] C.-C. Chen, W.-J. Huang, J.F. Petrick. 2016. Holiday recovery experiences, tourism satisfaction and life satisfaction – is there a relationship? Tourism Management, 53, pp. 140-147.
[32] J. Tribe, T. Snaith. 1998. From servqual to holsat: Holiday satisfaction in varadero, cuba, Tourism Management, 19(1), pp. 25-34.
[33] S. Gyimóthy. 2000. Visitors' perceptions of holiday experiences and service providers: An exploratory study, Journal of Travel & Tourism Marketing, 8(2), pp. 57-74.
[34] K. Yuan, L. Zheng, Q. Zhu. 2006. Are investors moonstruck? Lunar phases and stock returns, Journal of Empirical Finance, 13(1), pp. 1-23.
[35] P.-Y. Chen, Y. Hong, Y. Liu. 2018. The value of multidimensional rating systems: Evidence from a natural experiment and randomized experiments, Management Science, 64(10), pp. 4629-4647.
[36] H. Li, Z. Zhang, F. Meng, Z. Zhang. 2019. "When you write review" matters, International Journal of Contemporary Hospitality Management, 31(3), pp. 1273-1291.
[37] L. Deng, H. Hong, Q. Ye. 2019. Air pollution and online customer reviews: Evidence from restaurant reviews, in Proceedings of the 23rd Pacific Asia Conference on Information Systems (PACIS). Xi'an, China.
[38] J. Fang, L. Hu, M.A. Hossin, J. Yang, Y. Shao. 2019. Polluted online reviews: The effect of air pollution on reviewer behavior, International Journal of Electronic Commerce, 23(4), pp. 557-594.
[39] P.-H. Tan, C. Chou, J.-Y. Liang, C.C.K. Chou, C.-J. Shiu. 2009. Air pollution "holiday effect" resulting from the Chinese New Year, Atmospheric Environment, 43(13), pp. 2114-2124.
[40] P. Filiatrault, J.R.B. Ritchie. 1980. Joint purchasing decisions: A comparison of influence structure in family and couple decision-making units, Journal of Consumer Research, 7(2), pp. 131-140.
[41] S. Ransbotham, N.H. Lurie, H. Liu. 2019. Creation and consumption of mobile word of mouth: How are mobile reviews different? Marketing Science, 38(5), pp. 773-792.
[42] C.H. Mason, W.D. Perreault Jr. 1991. Collinearity, power, and interpretation of multiple regression analysis, Journal of Marketing Research, 28(3), pp. 268-280.
[43] D. Ein-Gar. 2015. Committing under the shadow of tomorrow: Self-control and commitment to future virtuous behaviors, Journal of Consumer Psychology, 25(2), pp. 268-285.
[44] Y. Liu, S. Segev, M.E. Villar. 2017. Comparing two mechanisms for green consumption: Cognitive-affect behavior vs theory of reasoned action, Journal of Consumer Marketing, 34(5), pp. 442-454.
[45] D. Talmi, C. Frith. 2007. Neurobiology: Feeling right about doing right, Nature, 446(7138), pp. 865-866.
[46] B. De Martino, D. Kumaran, B. Seymour, R.J. Dolan. 2006. Frames, biases, and rational decision-making in the human brain, Science, 313(5787), pp. 684-687.
[47] N. Huang, G. Burtch, Y. Hong, E. Polman. 2016. Effects of multiple psychological distances on construal and consumer evaluation: A field study of online reviews, Journal of Consumer Psychology, 26(4), pp. 474-482.
[48] M. Gorlin, R. Dhar. 2012. Bridging the gap between joint and individual decisions: Deconstructing preferences in relationships, Journal of Consumer Psychology, 22(3), pp. 320-323.
[49] Y. Hong, N. Huang, G. Burtch, C. Li. 2016. Culture, conformity, and emotional suppression in online reviews, Journal of the Association for Information Systems, 17(11), pp. 737-758.
[50] R. Gao, B. Hao, H. Li, Y. Gao, T. Zhu. 2013. Developing simplified Chinese psychological linguistic analysis dictionary for microblog, in Proceedings of the 2013 International Conference on Brain and Health Informatics. Cham: Springer.
[51] D. Nahl, C. Tenopir. 1996. Affective and cognitive searching behavior of novice end - users of a full - text database, Journal of the American Society for Information Science, 47(4), pp. 276-286.