Herding Behavior in Online Restaurant Ratings: Moderating Effects of Reviewer Popularity and Observed Review Volume

DaPeng Xu
School of Management, Harbin Institute of Technology, China, dpxu@hit.edu.cn

Hong Hong
School of Management, Harbin Institute of Technology, China, honghong@hit.edu.cn

Xu, D. & Hong, H. (2021). Herding behavior in online restaurant ratings: Moderating effects of reviewer popularity and observed review volume. In *Proceedings of The International Conference on Electronic Business, Volume 21* (pp. 208-216). ICEB'21, Nanjing, China, December 3-7, 2021.

Herding Behavior in Online Restaurant Ratings: Moderating Effects of Reviewer Popularity and Observed Review Volume

DaPeng Xu [1]
Hong Hong [2,*]

*Corresponding author
[1] Postdoctoral Research Associate, School of Management, Harbin Institute of Technology, China, dpxu@hit.edu.cn
[2] Associate Professor, School of Management, Harbin Institute of Technology, China, honghong@hit.edu.cn

ABSTRACT

Understanding the generation of online reviews is fundamental work for retailers to better utilize them. Review rating is the most important component of an online review; therefore, our study tries to investigate the antecedents of online reviews by figuring out the relationship between a reviewer's observed review rating and his/her rating. More specifically, this study aims to answer the following three research questions: (1) Does herding behavior exist in online ratings, i.e., is a reviewer's rating affected by his/her observed ratings given by other reviewers? (2) Does the observed review number moderate the direct effect of observed review ratings on a reviewer's rating behavior? (3) Does a reviewer's popularity moderate the direct effect of observed review ratings on his/her rating behavior? To answer these research questions, we conduct multiple empirical analyses using online restaurant reviews obtained from the most popular review platform in China. The results show that herding behavior does exist in online rating behavior. To be more specific, a reviewer's observed review rating while authoring reviews are positively related to his/her review rating; The observed review volume of the rated restaurant can mitigate the positive relationship between a reviewer's observed review rating and his/her rating. A reviewer's popularity can also mitigate the positive relationship between his/her observed review rating and his/her own rating. Our study makes contributions to both academic literature and managerial practice by demonstrating the presence of herding behavior in online review ratings. Our findings offer important implications for online review platform managers, product retailers, and consumers.

Keywords: User-generated content, online reviews, online rating behavior, herding behavior, moderating effects.

INTRODUCTION

The fast development of Web 2.0 and social media in the last decade has offered fertile ground for the emergence and accumulation of user-generated content (UGC). Among different types of UGC, online reviews are the most important form and are widely utilized by both consumers and retailers. For consumers, online reviews are treated as a trustworthy channel to obtain product information (Goh, Heng, & Lin, 2013). For retailers, it is a good way to know consumers' assessment and potential needs for the product or service (Zhou et al., 2018). Therefore, many businesses utilize online reviews as a new marketing strategy (Chen & Xie, 2008). Because of the widely recognized value of online reviews, both e-commerce researchers and practitioners pay increasingly more attention to this field.

Based on this background, understanding the generation of online reviews has become an essential task for practitioners to better utilize online reviews. To enrich studies on this topic, we will focus on the herding behavior in online review ratings. More specifically, this study aims to investigate the following three research questions: (1) Does herding behavior exist in online ratings, i.e., is a reviewer's rating affected by his/her observed ratings given by other reviewers? (2) Does the observed review number moderate the direct effect of observed review ratings on a reviewer's rating behavior? (3) Does a reviewer's popularity moderate the direct effect of observed review ratings on his/her rating behavior? To answer these research questions, we conducted several empirical analyses using online restaurant reviews collected from *PublicComments*, which is the most representative restaurant review platform in China.

We first establish the herding behavior effect using ordered logit regression. After identifying the herding behavior effect, we extend the model to check whether observed review volume and reviewer popularity on the platform can influence this effect. In addition to the main analysis, we conduct a series of robustness checks to confirm the generalizability of the results.

Our study yields the following findings. First, herding behavior does exist in online rating behavior. To be more specific, a reviewer's observed review rating while providing a review for a restaurant is positively related to his/her own rating for the restaurant. Second, the observed review volume of a restaurant can mitigate the positive relationship between a reviewer's observed review rating of the restaurant and his/her rating. Third, a reviewer's popularity can mitigate the positive relationship between his/her observed review rating of a restaurant and his/her own rating for the restaurant as well.

The remaining of this paper is structured as follows. We review related literature on consumers' online rating behavior and clarify herding behavior in the information systems (IS) domain, and then develop our hypotheses in Section 2. We describe our methodology, including data collection, variable measurement, and empirical model in Section 3. Then our result analyses are reported in the following section. In the final section, we conclude this paper by discussing the main findings, implications, and limitations of our study.

THEORETICAL BACKGROUND AND HYPOTHESES

Theoretical Background

Online rating behavior

To better utilize online reviews, it is essential for both practitioners and researchers to understand the generation of online reviews (Gao, Li, Liu, & Fang, 2018). Usually, an online review includes two components: an open-ended review text comment and a five-scale star rating (Mudambi & Schuff, 2010). Between the two components, star ratings are treated more important; therefore, most existing studies on online review generation mainly focus on consumers' online rating behavior (Gao et al., 2018; Ho, Wu, & Tan, 2017; Li, 2016; Zhang, Zhang, & Yang, 2016). To be more specific, Gao et al. (2018) study the influence of reviewers' power distance on reviewers' online rating behavior and obtain a negative relationship between them. Zhang et al. (2016) identify the relationship between expert reviews and travelers' rating behavior. Moe and Trusov (2011) confirm the social influence or herding behavior in online ratings, i.e., consumers' ratings can be influenced by previous ratings. Social influence can be further divided into friends' influence and non-friends influence. Lee, Hosanagar, and Tan (2015) investigate the different impacts of friends' and non-friends social influence on reviewers' ratings and find user ratings always herd with friends' ratings but differentiate from non-friends ratings for niche movies. Wang, Zhang, and Hann (2018) empirically examine online friends' social influence bias in online book ratings by finding a significantly higher rating similarity after reviewers becoming online friends. Building on this stream of research, our study investigates herding behavior in online ratings in depth.

Herding behavior

Herding behavior refers to the phenomenon that "everyone does what everyone else is doing, even when their private information suggests doing something quite different" (Banerjee, 1992). Herding is likely to occur when individuals do not have to compete for information or face uncertain situations (Walden & Browne, 2009). Prior studies have confirmed the presence of herding behavior in a wide range of situations, such as imitating other investors' behavior while investing (Hirshleifer, Subrahmanyam, & Titman, 1994), downloading software products (Duan, Gu, & Whinston, 2009), or adopting new information systems (Sun, 2013) following others. In the context of online review generation, some reviewers are uncertain about the quality of the reviewed product or service, and these reviewers are easy to be influenced by existing reviews. Therefore, herding behavior occurs in writing online reviews.

Hypotheses Development

Herding behavior in online review ratings

On a review platform, it is common to show the average rating of existing ratings, which we call an observed rating in this study. A reviewer knows the overall assessment of the product from this information cue, and this may cause the effects of social influence (Sridhar & Srinivasan, 2012), especially for reviewers who are uncertain about his/her own assessment. We believe a reviewer will be influenced by existing ratings and is prone to follow others' ratings while providing online ratings. Hence, we put forward the first hypothesis:

H1: When a reviewer provides an online review for a restaurant, the rating given by him/her is positively related to the observed average rating of the restaurant.

Moderating effect of observed review volume

Typically, a review platform also shows the information of how many reviews have been given to the product or service. This information cue may influence consumers' rating behavior. According to the attention-grabbing theory, in order to attract attention from review readers, online reviewers are prone to differentiate from the average rating if the observed review volume for the rated product is large (Shen, Hu, & Ulmer, 2015). Therefore, we argue that the observed review volume for the rated product can mitigate the herding behavior in online ratings and put forward the following hypothesis:

H2: The observed review volume of a restaurant weakens the relationship between the reviewer's observed average rating of the restaurant and the rating given by him/her.

Moderating effect of reviewer popularity

Most review websites allow users to interact with each other by following others. Reviewers with more fans or followers usually have more experience and know-how to behave smartly to attract more attention and fans. Negative reviews are treated more helpful by readers, so negative reviews will attract more users' attention. As reviewers become more popular, their numerical review ratings become more negative (Goes, Lin, & Au Yeung, 2014). For reviewers with low popularity, they may not know the way to act smartly to obtain more followers, or they do not want to, so they are less likely to provide lower ratings and more likely to be influenced by existing ratings; while for those with more fans, they are more experienced to know how to attract more followers. Hence they tend to provide lower ratings and less be likely to be impacted by existing ratings. Therefore, we put forward the following hypothesis:

H3: The popularity of a reviewer weakens the relationship between his/her observed average rating of a restaurant and the rating given by him/her to the restaurant.

Our research model is illustrated in Figure 1 below.

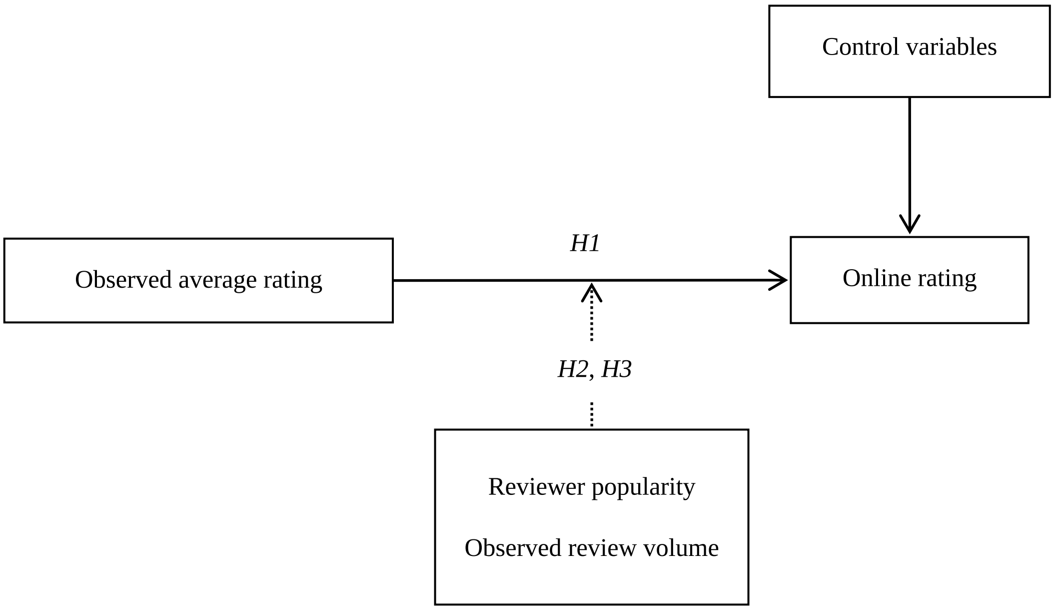

Figure 1: Research model.

METHODOLOGY

Data

The main data source of this study is the most popular reputation platform in China, which we designate an alias as *PublicComments* for anonymity purposes. We first developed a web crawler and collected data of reviews for a set of restaurants from it, spanning the period between 2004 and 2017. For the restaurant sample, we randomly selected ten major cities in China (Amoy, Changsha, Chengtu, Dalny, Harbin, Kunming, Sanya, Tsingtao, Xi'an, and Xining). In this study, we just collected review data for ten restaurants with the largest numbers of online reviews for each city in order to improve the efficiency of data collection. Every consumer review for a restaurant since the restaurant is added to the platform was collected. Each review contains a timestamp and review content (an overall rating, three sub-ratings, text, and pictures, etc.) in addition to the reviewer- and restaurant-related information. After dropping the observations with missing data, 87,895 reviews were included in our main analysis, while 92,106 in the robustness check.

Variables and Measures

Dependent variable

Following prior research (Gao et al., 2018; Ho *et al.*, 2017; Li, 2016; Zhang *et al.*, 2016), we adopt review rating as the dependent variable. It is an integer and ranges from 1 to 5 based on the five-star rating scale of *PublicComments*. More stars indicate more positivity, and one star represents the worst evaluation for a product or service. In general, the review rating given by a consumer can be used to indicate his/her satisfaction with the product or service (Gu & Ye, 2014).

Independent variable

When a reviewer provides a review for a restaurant where s/he had dinner, the average rating aggregated from pre-existing reviews of the restaurant can be explicitly observed by him/her. In this study, we use it as the independent variable and name it *obsAvgRating*.

Moderating variables

The variables of *reviewerPopularity* (measured by the number of fans owned by a reviewer on the platform) and *obsReviewVolume* (measured by the number of pre-existing reviews of a restaurant observed by a reviewer when s/he provides a review for the restaurant) are treated as moderator variables in our study.

Control Variables

To robustly test our research hypotheses, we also include a comprehensive set of control variables in addition to the key variables mentioned above. The variable of *consumPerPerson* is measured by the per capita cost disclosed by the reviewer in a review. The variable of *travelReview* is a binary variable, and it is equal to zero if the city of residence disclosed in the reviewer's profile and the city where the restaurant is located the same and 1 otherwise. The variable of *vipReviewer* is also a binary variable to indicate whether the reviewer has been approved to be a VIP user by the platform. The variable of *reviewerEconStatus* is measured by the average annual GDP per capita from 2005 to 2015 of the reviewer's residence city to reflect his/her regional economic status. The economic data can be obtained from the CEIC database (https://insights.ceicdata.com/). The variable of *reviewerActivity* is measured by the ratio of the number of restaurants reviews the reviewer has posted on the platform to the number of days the reviewer has experienced since s/he signed up as a registered user of the platform. Moreover, we also control for the fixed effects of restaurants (*restaurantFE*) in our analysis.

We present all the variables and their measurement in Table 1. In order to reduce skewness, natural log-transformations are adopted for the variables of *obsReviewVolume*, *consumPerPerson*, *reviewerPopularity*, and *reviewerActivity*. Besides, the GDP data are in a unit of 100,000 RMB.

Table 1: Variable description.

Variable Type	Variable	Description
Dependent variable	*rating*	The overall rating of a restaurant given by a reviewer (ordered variable with five cases: 1, 2, 3, 4, and 5).
Independent variable	*obsAvgRating*	A restaurant's average rating at the time was just before a reviewer provided the focal review.
Moderating variable	*reviewerPopularity*	The number of followers owned by a reviewer.
	obsReviewVolume	The number of a restaurant's reviews at the time just before a reviewer provided the focal review.
Control variable	*consumPerPerson*	The per capita cost was disclosed by the reviewer in the review.
	travelReview	A binary variable, which equals 0 if the city of residence disclosed by the reviewer on his/her homepage and the city where the restaurant is located the same, and 1 otherwise.
	vipReviewer	A binary variable indicating whether the reviewer has been recognized as a VIP user of the platform.
	reviewerEconStatus	It is measured by the average annual GDP per capita from 2005 to 2015 of the reviewer's residence city.
	reviewerActivity	They are measured by the ratio of the number of restaurant reviews the reviewer has posted to the number of days the reviewer has experienced since s/he signed up as a registered user of the platform.
	restaurantFE	The fixed effects of the restaurants.

Empirical Model

Given the nature of the dependent variable, which is a discrete, ordered, and censored variable, we choose to employ an ordered logistic regression model following previous literature (Gao et al., 2018; Huang, Burtch, Hong, & Polman, 2016) to estimate the results.

RESULTS

Descriptive Analysis

Table 2 and Table 3 report the descriptive statistics and correlation matrix for the main variables in our study, respectively. It is worth noting that we just report the original value of *obsReviewVolume*, *consumPerPerson*, *reviewerPopularity*, and *reviewerActivity* in the descriptive statistics to better provide a more intuitive description of the data set, whereas we take a natural log conversion for these variables in the correlation analysis and the regression analyses due to their large skewness. As we can see from Table 2, the data set is representative.

Table 3 provides the correlation matrix of the main variables in our study. As we can see from the correlation matrix, all the correlations between the two variables are small and below 0.5. To further rule out the multicollinearity issue, we calculated the variance inflation factor (VIF) values for all independent variables. All the VIF values are far below 5, indicating that multicollinearity is not a threat to our study.

Table 2: Descriptive Statistics of Variables.

Variable	Obs#	Mean	Std. Dev.	Min	Max
rating	104,581	4.228	1.002	1	5
obsAvgRating		4.224	0.417	1	5
reviewerPopularity		44.439	147.786	0	9,467
obsReviewVolume		3,994.941	3,478.877	1	22,379
consumPerPerson		141.823	6,536.737	1	1,000,000
travelReview		0.624	0.484	0	1
vipReviewer		0.223	0.416	0	1
reviewerEconStatus		0.649	0.181	0.068	1.391
reviewerActivity		0.442	6.572	0.000	880

Table 3: Correlation Matrix and VIF Values of Main Variables.

	1	2	3	4	5	6	7	8	9	10	VIF
2	0.339										1.45
3	0.129	0.370									1.40
4	-0.120	-0.415	-0.474								1.42
5	0.050	0.230	0.082	-0.023							1.07
6	0.006	-0.045	0.081	-0.048	0.000						1.27
7	-0.072	-0.019	0.090	-0.037	-0.031	0.005					1.33
8	0.026	0.062	0.060	-0.048	0.007	0.435	0.011				1.25
9	-0.064	-0.062	0.004	0.001	-0.017	0.052	0.479	0.067			1.40
10	0.072	0.242	0.064	-0.077	0.107	-0.087	-0.137	-0.036	-0.274		1.16
11	-0.104	-0.219	-0.180	0.121	-0.096	-0.077	0.179	-0.070	0.182	-0.139	1.13

Notes: 1: *rating*; 2: *obsAvgRating*; 3: *obsReviewVolume*; 4: *obsAvgRating* × *obsReviewVolume*; 5: *consumPerPerson*; 6: *travelReview*; 7: *vipReviewer*; 8: *reviewerEconStatus*; 9: *reviewerPopularity*; 10: *obsAvgRating* × *reviewerPopularity*; 11: *reviewerActivity*.

Main Analysis

Following the common practice, in order to avoid nonessential multicollinearity between a variable and its corresponding interaction term(s), the moderating variables (i.e., *obsReviewVolume* and *reviewerPopularity*) and the independent variable (i.e., *obsAvgRating*) were centered by subtracting their respective mean values to obtain the interaction term of a moderating variable and the independent variable in the regression analyses (Cohen, Cohen, West, & Aiken, 2003). We report the estimation results of our main analysis in Table 4.

After taking the effects of all control variables into account, we can find that a significantly positive relationship does exist between the dependent variable and the independent variable (*b*=0.761***). This result supports the hypothesis of *H1*, indicating that the higher the observed average rating of a restaurant, the higher an online rating will be given by the focal reviewer to the restaurant.

The interaction terms are also significant, implying that the marginal effect of observed average rating on online rating depends on the reviewer's popularity and his/her observed review volume of the restaurant. Specifically, the positive influence of the observed average rating on the focal rating is weaker for reviewers with more followers or restaurants with more existing reviews. As such, both of the other two hypotheses, *H2* and *H3*, are also supported.

Table 4: Main Results.

	Model 1	Model 2	Model 3
obsAvgRating		**0.761*** (0.035)**	**0.680*** (0.041)**
obsReviewVolume	0.272*** (0.006)	0.175*** (0.007)	0.167*** (0.007)
obsAvgRating × *obsReviewVolume*			**-0.082*** (0.015)**
consumPerPerson	-0.347*** (0.018)	-0.338*** (0.018)	-0.335*** (0.018)
travelReview	0.164*** (0.020)	0.167*** (0.020)	0.156*** (0.020)
vipReviewer	-0.402*** (0.017)	-0.398*** (0.017)	-0.398*** (0.016)
reviewerEconStatus	-0.146** (0.048)	-0.156** (0.049)	-0.153** (0.049)
reviewerPopularity	-0.025*** (0.005)	-0.025*** (0.005)	-0.045*** (0.005)
obsAvgRating × *reviewerPopularity*			**-0.115*** (0.009)**
reviewerActivity	-0.109*** (0.017)	-0.100*** (0.017)	-0.106*** (0.017)
restaurantFE	Yes	Yes	Yes
Constant Cut 1	-3.312*** (0.116)	-0.756*** (0.166)	-1.247*** (0.200)
Constant Cut 2	-2.441*** (0.115)	0.116 (0.165)	-0.374 (0.200)
Constant Cut 3	-1.024*** (0.115)	1.537*** (0.165)	1.048*** (0.200)

Constant Cut 4	0.599*** (0.115)	3.167*** (0.166)	2.681*** (0.200)
Observations	87,913	87,895	87,895

Notes: Cut *i* is the cut-point corresponding to the ordered category of online ratings; robust standard errors are included in parentheses; **: p<0.01, ***: p<0.001.

Robustness Checks

We investigate the robustness of our results in two different ways: (1) Utilizing alternative measurement for key variables; and (2) utilizing alternative estimation method.

Robustness check with alternative measurement

We verify the robustness of our results with alternative measurements for the dependent and independent variables. As mentioned earlier, besides an overall rating for the restaurant in a review, users can also provide a rating on three sub-dimensions (taste of the food, restaurant environment, and service quality). In order to utilize the trait of such a multi-dimensional rating system, we converted the measurement of the dependent variable from the overall rating to the three sub-ratings and that of the independent variable from the observed average overall rating to the observed average sub-ratings to re-conduct corresponding analyses. Table 5 presents the results estimated with the three alternative, dependent variables, and corresponding independent variables. The results are remarkably consistent with the results from the main analysis, demonstrating the solid robustness of our research findings.

Table 5: Results of Robustness Check-in Sub-rating Dimensions.

	DV: *tasteRating*	DV: *environmentRating*	DV: *serviceRating*
obsAvgRating	**0.503***** **(0.016)**	**0.586***** **(0.014)**	**0.556***** **(0.012)**
obsReviewVolume	0.090*** (0.008)	0.053*** (0.007)	0.057*** (0.008)
obsAvgRating × *obsReviewVolume*	**-0.034***** **(0.004)**	**-0.053***** **(0.003)**	**-0.039***** **(0.003)**
consumPerPerson	-0.233*** (0.017)	-0.250*** (0.018)	-0.237*** (0.017)
travelReview	0.143*** (0.019)	0.136*** (0.019)	0.153*** (0.019)
vipReviewer	-0.392*** (0.016)	-0.354*** (0.016)	-0.318*** (0.016)
reviewerEconStatus	-0.107* (0.047)	-0.253*** (0.047)	-0.169*** (0.047)
reviewerPopularity	-0.046*** (0.005)	-0.052*** (0.005)	-0.061*** (0.005)
obsAvgRating × *reviewerPopularity*	**-0.029***** **(0.003)**	**-0.019***** **(0.002)**	**-0.024***** **(0.002)**
reviewerActivity	-0.038** (0.015)	-0.069*** (0.015)	-0.083*** (0.014)
restaurantFE	Yes	Yes	Yes
Constant Cut 1	-0.881*** (0.153)	-1.410*** (0.147)	-0.910*** (0.135)
Constant Cut 2	0.782*** (0.152)	0.867*** (0.146)	0.879*** (0.134)
Constant Cut 3	2.123*** (0.152)	2.298*** (0.147)	2.172*** (0.135)
Constant Cut 4	3.606*** (0.153)	3.812*** (0.147)	3.521*** (0.135)
Observations	92,085	91,005	92,106

Notes: Cut *i* is the cut-point corresponding to the ordered category of online ratings; robust standard errors are included in parentheses; *: p<0.05, **: p<0.01, ***: p<0.001.

Robustness check with an alternative method

To further investigate the robustness of the results from another angle, we conducted linear regression analyses with ordinary least squares (OLS) estimates in the overall rating dimension and three sub-rating dimensions. The corresponding results are displayed in Table 6. As we can see, the relationships between the focal variable as well as other control variables and the dependent variable still hold in all the four rating dimensions.

Table 6. Results of Robustness Check with OLS Estimates.

	DV: *rating*	DV: *tasteRating*	DV: *environmentRating*	DV: *serviceRating*
obsAvgRating	**0.275*** (0.021)**	**0.228*** (0.008)**	**0.281*** (0.007)**	**0.287*** (0.007)**
obsReviewVolume	0.068*** (0.003)	0.039*** (0.004)	0.016*** (0.003)	0.023*** (0.004)
obsAvgRating × *obsReviewVolume*	**-0.064*** (0.009)**	**-0.029*** (0.002)**	**-0.035*** (0.001)**	**-0.032*** (0.001)**
consumPerPerson	-0.179*** (0.009)	-0.130*** (0.009)	-0.127*** (0.008)	-0.129*** (0.009)
travelReview	0.051*** (0.009)	0.053*** (0.009)	0.047*** (0.008)	0.059*** (0.009)
vipReviewer	-0.121*** (0.008)	-0.142*** (0.008)	-0.126*** (0.008)	-0.118*** (0.008)
reviewerEconStatus	-0.082*** (0.022)	-0.054* (0.022)	-0.118*** (0.021)	-0.087*** (0.023)
reviewerPopularity	-0.008*** (0.002)	-0.011*** (0.002)	-0.015*** (0.002)	-0.020*** (0.002)
obsAvgRating × *reviewerPopularity*	**-0.039*** (0.005)**	**-0.008*** (0.001)**	**-0.005*** (0.001)**	**-0.007*** (0.001)**
reviewerActivity	-0.035*** (0.009)	-0.011 (0.009)	-0.036*** (0.008)	-0.042*** (0.008)
restaurantFE	Yes	Yes	Yes	Yes
Constant	3.369*** (0.099)	1.711*** (0.079)	1.525*** (0.070)	1.472*** (0.071)
Observations	87,895	92,085	91,005	92,106
R-squared	0.149	0.214	0.356	0.323

Notes: Cut *i* is the cut-point corresponding to the ordered category of online ratings; robust standard errors are included in parentheses; *: p<0.05, ***: p<0.001.

CONCLUSION AND DISCUSSIONS

Main Findings

The main purpose of this study is to confirm the herding behavior in online ratings and figure out the moderating effects of product and reviewer characteristics. *PublicComments*, which is the most popular restaurant review platform, provides us with an appropriate context to answer the above-mentioned research questions. We first test the herding behavior effect using ordered logit regression. After confirming the presence of herding behavior, we apply another regression to check whether observed restaurant review volume and reviewer popularity influence this effect, and then we conduct robustness checks using alternative measurement for the dependent and independent variables and an alternative estimation method. The results of the hypotheses testing are reported in Table 7.

Our results show that herding behavior does exist in online rating behavior. To be more specific, a reviewer's observed review rating while authoring reviews is positively related to his/her review rating. The observed review volume of a restaurant can mitigate the positive relationship between a reviewer's observed review rating of the restaurant and his/her rating; a reviewer's popularity can also mitigate the positive relationship between the reviewer's observed review rating and his/her rating.

Table 7: Summary of Hypotheses Testing.

Hypothesis	Result
H1: When a reviewer provides an online review for a restaurant, the rating given by him/her is positively related to the observed average rating of the restaurant.	Supported
H2: The observed review volume of a restaurant weakens the relationship between the reviewer's observed average rating of the restaurant and the rating given by him/her.	Supported
H3: The popularity of a reviewer weakens the relationship between his/her observed average rating of a restaurant and the rating given by him/her to the restaurant.	Supported

Implications

Our study has both theoretical and practical implications. From the theoretical perspective, this study enriches research on online review generation. Given that understanding online review generation is a fundamental process for retailers to take advantage of online reviews, it is essential to identify factors influencing the generation of online reviews, especially online ratings. We confirm the herding behavior in online restaurant ratings and make some attempts to find out the mechanism behind it.

From the practical angle, our research findings are helpful for review platform managers to design better review rating systems and useful for consumers to understand online ratings better. Our study suggests that reviewers tend to provide higher ratings for restaurants with higher observed ratings, especially for restaurants with fewer reviews and reviewers with fewer fans. Therefore, it is advisable for platform managers to show average ratings differently for products with different popularity. To avoid reviewers being influenced by existing ratings, maybe the platform should avoid showing the review volume for niche products.

Limitations and Future Work

This study has some inherent limitations. First, we adopt a simple sampling method in this study. More specifically, to improve the efficiency of data collection, we just included ten restaurants in 10 randomly selected cities, which may impact the generalizability of this study. Future research should include more restaurants in studies, especially those with relatively less popularity. Second, we just test our research hypotheses in the catering business context, and we can further test the online reviewers' herding behavior in other contexts, such as the hotel industry, to achieve better generalizability. Third, besides the popularity levels of restaurants or reviewers, there are many other factors influencing online reviewers' herding behavior. Therefore, it is essential to investigate more mechanisms behind reviewers' herding behavior in future work.

ACKNOWLEDGMENT

This work was partially supported by the National Natural Science Foundation of China (Grant # 71801063) and the China Postdoctoral Science Foundation (Grant # 2018M640300).

REFERENCES

Banerjee, A. V. (1992). A simple model of herd behavior. *Quarterly Journal of Economics, 107*(3), 797-817. https://doi.org/10.2307/2118364

Chen, Y., & Xie, J. (2008). Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science, 54*(3), 477-491. https://doi.org/10.1287/mnsc.1070.0810

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*. New Jersey: Routledge.

Duan, W., Gu, B., & Whinston, A. B. (2009). Informational cascades and software adoption on the internet: An empirical investigation. *MIS Quarterly, 33*(1), 23-48. https://doi.org/10.2307/20650277

Gao, B., Li, X., Liu, S., & Fang, D. (2018). How power distance affects online hotel ratings: The positive moderating roles of hotel chain and reviewers' travel experience. *Tourism Management, 65*, 176-186. https://doi.org/10.1016/j.tourman.2017.10.007

Goes, P. B., Lin, M., & Au Yeung, C.-m. (2014). Popularity effect" in user-generated content: Evidence from online product reviews. *Information Systems Research, 25*(2), 222-238. https://doi.org/10.1287/isre.2013.0512

Goh, K.-Y., Heng, C.-S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user- and marketer-generated content. *Information Systems Research, 24*(1), 88-107. https://doi.org/10.1287/isre.1120.0469

Gu, B., & Ye, Q. (2014). First step in social media: Measuring the influence of online management responses on customer satisfaction. *Production and Operations Management, 23*(4), 570-582. https://doi.org/10.1111/poms.12043

Hirshleifer, D., Subrahmanyam, A., & Titman, S. (1994). Security analysis and trading patterns when some investors receive information before others. *The Journal of Finance, 49*(5), 1665-1698. https://doi.org/10.1111/j.1540-6261.1994.tb04777.x

Ho, Y.-C., Wu, J., & Tan, Y. (2017). Disconfirmation effect on online rating behavior: A structural model. *Information Systems Research, 28*(3), 626-642. https://doi.org/10.1287/isre.2017.0694

Huang, N., Burtch, G., Hong, Y., & Polman, E. (2016). Effects of multiple psychological distances on construal and consumer evaluation: A field study of online reviews. *Journal of Consumer Psychology, 26*(4), 474-482. https://doi.org/10.1016/j.jcps.2016.03.001

Lee, Y.-J., Hosanagar, K., & Tan, Y. (2015). Do I follow my friends or the crowd? Information cascades in online movie ratings. *Management Science, 61*(9), 2241-2258. https://doi.org/10.1287/mnsc.2014.2082

Li, X. (2016). Could deal promotion improve merchants' online reputations? The moderating role of prior reviews. *Journal of Management Information Systems, 33*(1), 171-201. https://doi.org/10.1080/07421222.2016.1172450

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research, 48*(3), 444-456. https://doi.org/10.1509/jmkr.48.3.444

Mudambi, S. M., & Schuff, D. (2010). What makes a helpful review? A study of customer reviews on Amazon.com. *MIS Quarterly, 34*(1), 185-200. https://doi.org/10.2307/20721420

Shen, W., Hu, Y. J., & Ulmer, J. R. (2015). Competing for attention: An empirical study of online reviewers' strategic behavior *MIS Quarterly, 39*(3), 683-696.

Sridhar, S., & Srinivasan, R. (2012). Social influence effects in online product ratings. *Journal of Marketing, 76*(5), 70-88. https://doi.org/10.1509/jm.10.0377

Sun, H. (2013). A longitudinal study of herd behavior in the adoption and continued use of technology. *MIS Quarterly, 37*(4), 1013-1041.

Walden, E. A., & Browne, G. J. (2009). Sequential adoption theory: A theory for understanding herding behavior in early adoption of novel technologies. *Journal of the Association for Information Systems, 10*(1), 31-62. https://doi.org/10.17705/1jais.00181

Wang, C. A., Zhang, X. M., & Hann, I.-H. H. (2018). Socially nudged: A quasi-experimental study of friends' social influence in online product ratings. *Information Systems Research, 29*(3), 641-655. https://doi.org/10.1287/isre.2017.0741

Zhang, Z., Zhang, Z., & Yang, Y. (2016). The power of expert identity: How website-recognized expert reviews influence travelers' online rating behavior. *Tourism Management, 55*, 15-24. https://doi.org/10.1016/j.tourman.2016.01.004

Zhou, S., Qiao, Z., Du, Q., Wang, G. A., Fan, W., & Yan, X. (2018). Measuring customer agility from online reviews using big data text analytics. *Journal of Management Information Systems, 35*(2), 510-539. https://doi.org/10.1080/07421222.2018.1451956