Why Is the Grass Always Greener on the Other Side? Tourist Bias in Online Restaurant Ratings

Dapeng Xu, Xiaoquan (Michael) Zhang, Hong Hong, Qiang Ye

Abstract: Online product and service ratings have great value for both sellers and consumers. Prior research, however, often treats online ratings equally even if the individuals who generate these ratings have very different backgrounds. This study examines how tourists differ from locals when they generate online ratings. We find that, relative to locals, tourists exhibit an upward bias when they rate restaurants visited on their trips. We explore possible mechanisms underlying this tourist bias. Based on data from an online review platform for restaurants, we first confirm the phenomenon of upward tourist bias in online ratings at both reviewer- and restaurant-level with multiple robustness checks. Then we conduct a series of analyses from reviewer-, restaurant-, cuisine- and city-level to identify factors leading to such a bias. We are able to examine the reasons related to consumption patterns such as restaurant price/service/environment, cuisine authenticity, tourists' evaluation process, differences between city sizes, etc. We find that individuals' change in focus (from location, cooking, and price to service, environment, and emotions) and change in the evaluation process (from cognitive to affective) can induce the tourist bias in ratings. We also discuss theoretical and practical implications for online review platforms, product retailers, and consumers.

Keywords: word-of-mouth; online review generation; online ratings; tourist bias

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1. Introduction

As consumer-generated evaluations for products or services posted on retailer or third-party websites, online ratings and reviews have become a prominent form of user-generated content that reduces consumption uncertainties (Dellarocas et al. 2007, Gottschalk and Mafael 2017). The popularity of online ratings has changed both the way consumers purchase products and the means for retailers to attract their consumers. Based on the report of BrightLocal, the majority of consumers (86%) read online reviews of local businesses before making shopping decisions (Murphy 2018). The volume, valence, and distribution features of online reviews can provide important information for consumers to select products and affect their decision making (Lu et al. 2022, Zhu and Zhang 2010). Retailers can also use online reviews to forecast product sales (Dellarocas et al. 2007, Duan et al. 2008, Liu 2006), identify product defects (Abrahams et al. 2015), develop new products (Zhou et al. 2018), and optimize pricing strategies (Feng et al. 2019).

An important assumption of online ratings' helpfulness is that rating valence can be a proxy for the quality of a product or service. However, individuals from different backgrounds may have different quality perceptions of the same product or service. For example, in an effort to match hotel ratings with individual needs, booking.com allows its visitors to focus only on ratings generated by a particular demographic group, such as business travelers, single travelers, or families with kids, or they can even sort the ratings according to the reviewers' home countries. While hotel reviews are almost all generated by travelers, restaurant reviews can come from two very different groups of customers: locals and tourists.

Ratings are not created equally by locals and tourists. Due to the intrinsic differences between these two groups of people, locals and tourists have very different expectations, tastes, experiences, tolerance levels, and ways of evaluation with respect to restaurants. As a result, review provision and consumption may follow different processes. Merely showing the average rating of a restaurant by pooling all ratings may not be very helpful for either visitors or locals who wish to find out if the restaurant is a good match.

On the consumption side, locals certainly do not want tourists' amateurish ratings to influence the quality assessment of local restaurants. At the same time, tourists may trade off the need to "eat like a local" (giving a greater weight to locals' ratings) and the need to find out how restaurants treat outsiders (giving a greater weight to travelers' ratings). Supporting this argument, Forman et al. (2008) find that online review readers rate reviews containing geographical location as being more helpful. Perhaps following this insight, Google Map gives restaurant reviews with "local guide" labels priority in the reviews of various points-of-interests. Unfortunately, no online restaurant review platforms have incorporated separate labels for reviews by travelers and locals so far.

On the provision side, ratings by locals are more likely to be based on the quality of the restaurant; but for travelers, ratings may also be decided by travelers' emotions, familiarity and taste compatibility with the food. Prior research establishes that psychological distance may change the positivity of online reviews (Huang et al. 2016). Associated with geographic distance, even the popularity difference between tourists' hometown and the city they visit can change how tourists write reviews (Kokkodis and Lappas (2020). Building on these prior works that show the existence of rating inflations related to traveling, we move forward to examine how and why tourists give higher ratings. We argue that such emotional, experiential, communicational, and economic factors can significantly influence how dining is experienced and eventually reported in the form of online reviews and ratings. This study offers a comprehensive empirical examination of how and why tourists' ratings are different from those by locals by investigating the impact of traveling on consumers' rating behavior.

Traveling is an experience-seeking process (MacKay and Fesenmaier 1997) through which travelers "consume places" (Haldrup and Larsen 2003). Tourist attractions usually offer something new and different, and this feeling of newness itself can spur consumers' affection for the place. Other than the indisputable "authenticity" of restaurants in the destination location, tourists may give higher ratings to destination restaurants simply for emotional reasons. Based on the theoretical foundation of emotion regulation (Gross 1998, 2008), travelers usually use emotion regulation to maximize their positive outcomes of their travel experiences (Gao and Kerstetter 2018). Therefore, travel often brings consumers with more positive emotions (Gao and Kerstetter 2018). Sirgy et al. (2011) also find that travel experience can improve individuals' overall life satisfaction, implying that everything else being equal, individuals on a trip may be more easily satisfied than those at home. Thus, we expect an upward bias in online ratings due to travel.

On the other hand, the relationship between travel and review ratings may be opposite based on the expectation-confirmation theory. As we know, consumers tend to visit popular and famous restaurants during traveling. Therefore, they usually have high expectations towards restaurants before the visit. However, high expectations can easily induce negative disconfirmation, which may result in consumers' lower ratings (Ho et al. 2017). Thus, we also examine a competing hypothesis that proposes a negative relationship between travel and review ratings.

We then investigate the potential mechanism underlying the locals-tourists difference in online ratings: (1) Can the tourist bias be attributable to consumers' consumption pattern change? (2) Will consumers' evaluation process change due to travel and does the difference in focus between tourists and locals lead to the bias? (3) Do cuisine authenticity and restaurant taste induce the tourist bias in online ratings? (4) Is the bias more salient for a certain sub-dimension of evaluation (taste, environment, or service)? To answer these questions, we conduct a series of empirical analyses based on online restaurant review data from a most popular review website in China.

We first establish the locals-tourists difference effect with an ordered logit regression. After identifying the tourist bias, we apply multiple regressions to check whether restaurant price, restaurant type, reviewer gender, and reviewer home city size may influence this effect and then examine potential mechanisms underlying this bias mentioned above by conducting a series of individual-, restaurant-, cuisine- and city-level analyses.

This study yields the following findings. First, we find that traveler consumers are at least 13.4% more likely than local consumers to provide a higher restaurant rating and they tend to attach more pictures, write shorter reviews, and use fewer cognitive words. Second, travel exerts a significant positive effect on ratings for both chain and independent restaurants across different restaurant price levels, and for both male and female reviewers from both small and large cities; the upward tourist bias still holds after controlling for time-variant restaurant features in a restaurant-level analysis. Third, individuals' change in focus (from location, cooking, and price to service, environment, and emotions) and change in evaluation process (from cognitive to affective) induce the tourist bias in ratings. At the same time, travel destination, restaurant cuisine authenticity, and consumers' consumption pattern change (e.g., visiting more upscale restaurants on trips) are not responsible for the tourist bias in online ratings.

Our study makes several theoretical and practical contributions. First, our research examines several potential underlying mechanisms behind the tourist bias. Our empirical framework helps us to rule out some alternative explanations of the observed rating inflations. Second, to make causal arguments, we propose a within-group study of reviewers and a between-group study of restaurants. Finally, from a practical perspective, our study demonstrates the necessity of differentiating travelers' and locals' ratings/reviews and identifies possible reasons behind the tourist bias to help practitioners better understand and utilize it. Our findings offer important implications for product and service providers, online review platforms, and consumers.

The rest of the paper is organized as follows. We review the existing literature related to travelers' behavior and consumers' online reviewing behavior, and then build the core research hypotheses in Section 2. The data collection process and research methodology are described in Section 3. In Section 4, we report and discuss the main empirical findings. Section 5 further examines the robustness of the findings and analyze related mechanisms. In Section 6, we conclude our study by discussing the implications, limitations and future research directions.

2. Literature Review and Hypotheses Development

2.1. Literature Review

Our study is related to the literature of online word-of-mouth (WOM) in general and online review generation in particular (Dellarocas 2006). We summarize the literature on the use and generation of online reviews in Appendix 1. The value of online WOM lies in its offering true information towards the assessed product or service. However, existing literature suggests that online ratings can be biased, and ratings generated under these mechanisms can cause social welfare losses (Hu et al. 2017, Wang et al. 2018, Lu et al. 2022). This stream of studies is closely related to our study; hence, we specially review the research on rating bias in detail in this section. Prior literature suggests that online ratings can be biased by self-selection, social influence, air quality and other factors. Factors inducing rating bias can be divided into two categories: reviewer-related factors and contextual factors.

For reviewer-related factors, self-selection is widely investigated. Li and Hitt (2008) find that the predominant declining trend of book ratings can be attributable to consumers' self-selection bias. In line with this study, Hu et al. (2009) further classify self-selection bias into acquisition bias (purchasing bias) and underreporting bias. Acquisition bias derives from the costs, including money, time or effort, in searching for the product (Hu et al. 2017). Those who exert costs are already the individuals who may like the products more than others. The underreporting bias exists because not all consumers write online reviews (Hu et al. 2017). Lin and Heng (2015) analyze the dynamic aspects of review ratings and find that extremely high ratings are more likely to attract negative ratings subsequently due to consumers' higher expectations. After analyzing a large data set of eBay feedback, Dellarocas and Wood (2008) confirm the existence of reporting bias and find that eBay traders are likely to post positive feedback or remain silent for fear of retaliation.

In addition to self-selection, reviewers' popularity and self-enhancement are found to bias review ratings as well. More specifically, reviewers' ratings become more negative and more varied when their popularity increases (Goes et al. 2014); self-enhancement leads reviewers to generate positive online ratings (Angelis et al. 2012).

In terms of contextual factors, social influence is widely examined. This stream of studies focuses on how visible previous ratings provided by others affect reviewers' ratings. Using an experimental method, Schlosser (2005) confirms the effects of previous opinions on reviewers. Moe and Trusov (2011) also show the existence of social influence in consumers' rating behavior utilizing real review data. Sridhar and Srinivasan (2012) investigate how social influence from other consumers moderates the relationship between reviewers' product experience and their rating behavior. Social influence can be further divided into friends' influence and strangers' influence. Lee et al. (2015) investigate the differential impact of friends' and strangers' influence on reviewers' ratings and find that user ratings always herd with friends' ratings but differentiate from non-friends' ratings for niche movies. Wang et al. (2018) empirically examine online friends' social influence bias in online book ratings by finding a significantly higher rating similarity after reviewers' becoming online friends.

The literature also identifies other factors, such as air quality, free product sampling, and distance, that bias ratings. Fang et al. (2019) find that air quality can influence reviewers' rating behavior: reviewers tend to provide relatively lower ratings while exposed in a high-pollution environment. Using review data obtained from Taobao, Lin et al. (2019) find that retailers engaging in free product sampling can lead to upward rating bias. Huang et al. (2016) find positive effects of spatial distance (the distance between reviewer's place of residence and the reviewed restaurant' location) and temporal distance (the time interval between consumption date and review date) on review ratings.

We summarize prior research on rating bias in Table A1 in Appendix 1. In line with this stream of studies, we study a new form of bias (i.e., tourist bias) in online ratings by investigating the influence of travel on ratings, and more importantly, uncovering the mechanisms behind it.

This work deepens our understanding of the effect reported in Huang et al. (2016), which identifies a psychological distance-related effect in online ratings. Our study is different from Huang et al. (2016) on several aspects. First, the mechanisms underlying the identified effects are different. Huang et al. (2016)'s focus is on psychological distance, so the bias arises from perceived spatial and temporal distance between the reviewer and the restaurant. We argue, instead, that there could be multiple alternative explanations for the identified inflation in tourist ratings, so our work comprehensively examines the emotional, experiential, communicational, and economic factors behind how travelers are fundamentally different from locals when giving ratings. For example, we examine consumers' change in consumption pattern and evaluation process and how restaurant taste, environment and service may affect their ratings. Second, the empirical frameworks are different and therefore the two studies answer different questions. Our dataset allows us to conduct nuanced reviewer-, restaurant-, cuisine-, and city-level analyses. Such a framework can cross-check the validity of the proposed mechanisms and suggests that psychological distance cannot fully explain the observed effect. In other words, while Huang et al. (2016) demonstrate the existence of rating inflation as a result of psychological distance, our work further explores the "why" question and seeks to understand the underlying mechanism. Third, given the differences in focus and in data, we are able to propose new research models such as within-group study based on reviewers, between-group study based on restaurants, cuisine-level and city-level comparisons, and natural language processing-based analysis to uncover reviewers' thinking process. These models offer powerful tools for further examination of the determinants of the effect.

Our work also extends and complements Kokkodis and Lappas (2020). They find a travel-related, popularity-difference bias. The popularity-difference bias is positive (negative) for reviewers traveling to a more (less) popular city than their city of residence. Since we focus more on investigating potential mechanisms underlying the bias, we are able to examine how the main effect can be affected by many other important factors. With our quasi-experimental framework, we find that all rating inflations are positive (i.e., travelers tend to give higher ratings than locals irrespective of the popularity difference between the two places). Our result is not inconsistent with theirs because we aim to answer different questions. We both find that tourists from less popular cities give higher ratings when they travel. They find that tourists from more popular cities give lower ratings when they visit less popular destinations, while we find that even tourists from more popular cities generally give higher ratings when they visit other cities (including both popular and less popular destinations).

Figure A1 in Appendix 2 shows the similarities and differences between our work and these two most closely related studies. Our proposed framework and comprehensive tests allow us to examine many potential alternative explanations that are missing from prior works. For example, we show that the inflation in tourist ratings is not caused by tourists' going to restaurants with higher prices, better services, or better environments. Our tests also rule out the possibility that the tourists may give higher ratings to restaurants of a travel destination simply because the cuisines are more authentic.

2.2. Hypotheses Development

2.2.1. Tourist Bias in Online Ratings

Consumers' behavior may be drastically different depending on whether consumers are in their home city or at a travel destination. Tour, which is defined as a short-term movement from individuals' normal place of their residence to travel destinations, is a service rather than a product in its nature, and its service nature exerts significant impacts on consumers' behavior during the consumption stage (Swarbrooke and Horner 2007). For example, March and Woodside (2005) identify an impulse buying effect. Consumer behavior research categorizes travel's effect into three stages: pre-consumption, consumption, and post-consumption (Frambach et al. 2007). Prior studies have confirmed the influence of travel on consumers' pre-consumption behavior (e.g., online information search), and consumers' consumption behavior (e.g., souvenir buying). However, how travel impacts consumers' evaluation behavior in the post-consumption stage is seldom investigated. The convergence of social media and travel has dramatically changed travelers' behavior, including information search and travel information sharing, making consumers important online information providers. Consumer-generated content makes it possible to investigate the relationship between travel and consumers' post-consumption behavior. We study how travel affects online rating behavior (i.e., the phenomenon of tourist bias) by investigating the influence of travel on ratings.

During the post-consumption stage, Internet technologies can be used to share, document, and relive travel experiences via storytelling (Gretzel et al. 2006). Nowadays, it is very common for travelers to share their hotel-staying experiences on trip review websites, such as TripAdvisor, and share their dining experiences on food review platforms, such as Yelp (Filieri 2016). It is common for consumers to write online reviews for the products and services that they have consumed, as visually sharing the experience with others is one of the best ways of combining isolated pieces of cognitive or sensory information into a logical whole, which can make the experience far more memorable (Gretzel et al. 2006). Consumer-generated content is particularly important in the hospitality and tourism industries, as these industries offer experience goods/services that are very difficult to evaluate before consumption (Litvin et al. 2008).

Emotion regulation is a psychological intervention that is widely adopted by tourists (Gao and Kerstetter 2018). It is a theoretical foundation of the manners that individuals manage what emotions they have, when they have them, and how they experience and express them (Gross 1998, 2008). Furthermore, it describes how consumers manage their emotions. According to Gao and Kerstetter (2018), travelers usually use emotion regulation to maximize the positive outcomes of their travel experiences. Drawing on their findings, travel often leads to consumers' positive emotions: from sad to happy or from happy to happier. Since social sharing of emotions (Rimé 2009) provides an important channel for consumers to regulate their emotions, travel usually brings consumers good mood, such as happiness and excitement, and this mood change caused by travel may impact consumers' rating behavior.

Specifically, traveling consumers' rating behavior may be different from those consumers who remain in their regular location of residence (Neumann et al. 2017). Hence, travelers' high arousal emotions can increase the valence of their WOM (Berger 2014). Meanwhile, online ratings can be used to indicate consumers' overall satisfaction with the product or service (Gu and Ye 2014). Sirgy et al. (2011) find that travel can impose a positive effect on individuals' overall well-being, implying that tourist consumers may be more satisfied than those at home. In addition, travel destination image also has a positive influence on tourists' overall satisfaction (Chi and Qu 2008, Pike 2002). Therefore, we put forward the following hypothesis:

H1a: Compared to locals, tourists tend to give higher ratings for the restaurants they visit on a trip.

On the other hand, according to the expectation-confirmation theory, the relationship between travel and review ratings may be opposite. The expectation-confirmation theory is a cognitive theory, which aims to explain consumers' satisfaction towards a product or service (Oliver 1977, 1980). Basically, this theory argues that the negative or positive disconfirmation between consumers' expectations and their perceived quality will affect consumers' post-purchase satisfaction (Anderson 1973). To be more specific, positive disconfirmation occurs when a product's quality outperforms consumers' expectations, resulting in satisfaction, whereas negative disconfirmation occurs when a product's quality is inferior to their expectations, inducing dissatisfaction (Anderson 1973).

Disconfirmation is found to affect consumers' rating behavior as well. More specifically, consumers tend to provide relatively higher ratings when they encounter positive disconfirmation; on the other hand, if consumers face negative disconfirmation, they are prone to give relatively lower ratings (Ho et al. 2017). In our research context, travelers may visit popular and famous restaurants. Before the visit, they may have high expectations towards the quality of the restaurants. However, the high expectations may be associated with disappointment. As popular restaurants often encounter excessive demand, so the long-time waiting and crowded environment may lead to negative disconfirmation, inducing lower satisfaction. Hence, we propose *H1b*, which is a competing hypothesis for *H1a*:

H1b: Compared to locals, tourists tend to give lower ratings for the restaurants they visit on a trip.

2.2.2. Reasons Behind the Tourist Bias

The above hypotheses are about the relationship between travel and ratings, i.e., the tourist bias. We will discuss factors inducing this tourist bias, i.e., the mechanism behind it, in the following. More specially, we discuss the potential reasons behind this bias from the perspective of consumers.

(1) Travel and Consumers' Consumption Pattern Change

Travel, a short-time movement from individuals' residence to travel destinations, can impact consumers' consumption behavior (Swarbrooke and Horner 2007), such as impulse buying behavior and souvenir shopping. It may give rise to a change in consumption pattern while traveling.

According to mental accounting, which is defined as "the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities" (Thaler 1999), individuals create multiple mental accounts to assign their budget for each account. Sussman and Alter (2012) divide expenses into ordinary mental account, which is common and frequent, and exceptional mental account, which is uncommon and infrequent. For ordinary expense account, such as expenses for food and rent, individuals reserve their budget for this essential expense. They also allocate some money for exceptional expense account, such as entertainment or travel. Therefore, consumers will prepare additional money for travel, which is not subject to the ordinary budget and will not affect their ordinary life. This may induce individuals to consume differently when at home and on travel. Usually, individuals consume more generously on journey than at home. As an old Chinese saying goes, be thrifty at home and spend liberally while travelling. In terms of our research context, consumers may visit better restaurants with higher prices during traveling.

In the context of product evaluation, product price may play an important role, because it can impact consumers' perceptions towards the product, and the difference between product quality and product price will impact consumers' satisfaction reflected by reviewers' ratings (Li and Hitt 2010). Consumers may engage in different post-consumption behaviors (e.g., assessment result of or satisfaction with the product), depending on how much money they paid for the product. Specifically, tourist consumers may give higher ratings for restaurants' higher quality or give lower ratings for higher expectations toward the restaurants caused by higher prices.

Besides restaurant price, restaurant service and restaurant environment levels can also be used to measure restaurant quality. Restaurant service, price, and environment are three restaurant features, which play important roles in tourists' selecting restaurants (Vu et al. 2017). As such, we conjecture that consumers on travel tend to visit restaurants with higher prices and better environment and service and such a consumption pattern change may be the reason for the tourist bias. Therefore, we put forward the following hypotheses:

H2a: Compared to locals, tourists tend to visit restaurants with higher prices.

H2b: Compared to locals, tourists tend to visit restaurants with better service.

H2c: Compared to locals, tourists tend to visit restaurants with better environment.

(2) Travel and Consumers' Evaluation Process Change

Besides rating behavior, travel is also likely to affect the way consumers write online reviews in terms of their change of evaluation process, e.g., their reliance on affective or cognitive mental processes. Affective (emotional) processes incorporate feelings associated with the entity being evaluated, whereas cognitive (rational) processes incorporate attributes and beliefs about the entity (Millar and Tesser 1986). If a consumer relies on cognitive processes when writing a review, s/he is likely to express the review with logical and analytical words, such as "think", "because", and "hence." Therefore, the change of consumers' evaluation process can be reflected by the review content, and this change may be responsible for the tourist bias.

Smartphones with powerful camera functions enable individuals to take pictures anytime and anywhere, making photo-sharing a common activity for consumers while providing online reviews. Particularly in the tourism industry, photo-sharing plays an essential role in travel experience sharing, as tour can be treated as a uniquely visual experience (MacKay and Fesenmaier 1997) about "consuming places" (Haldrup and Larsen 2003). It is indispensable for travelers to take photos to describe their relationships with unusual people, places, and cultures in travel destinations (Edensor 2000), making photos sent by smartphones a new postcard. Therefore, it is reasonable to argue that consumers on travel have a much stronger motivation to share what they experience during the trip using pictures than those who are at home. Hence, we propose *H3a*:

H3a: Compared to locals, tourists tend to provide reviews with more pictures.

According to the social psychology literature, affective and cognitive processes are negatively correlated (Pervin and John 1999). Therefore, while writing online reviews, consumers might be expected to rely on only one type of mental process (i.e., either affective or cognitive) (Huang et al. 2017). If a consumer relies on cognitive processes when writing a review, s/he is likely to express the review with logical and analytical words, whereas fewer words associated with emotions. Hence, we take the number of cognitive words out of the total number of words into account to measure the linguistic feature of online reviews.

Travel is likely to affect the way consumers write online reviews in terms of their reliance on affective or cognitive mental processes. When individuals experience the environment, their first-level response is affective, and the affective quality related to a place impacts their subsequent actions to the place (Ittelson 1973). Hence, consumers on travel may be more emotional than at home and are more likely to express themselves through affective processes, reducing the use of cognitive process words in their review texts. Hence, we posit the following hypothesis:

H3b: Compared to locals, tourists tend to write reviews with fewer cognitive words.

A short-term movement from individuals' place of residence to travel destinations makes tourists meet new people and have new experiences, motivating them to share what they experience during travel with others. Tourists often share not only knowledge-related information, such as prices and weather conditions, but also emotions and fantasies about the destination (Baym 2010). Therefore, tourist reviewers use multiple ways to express their experience during travels. As we mentioned above, tourist reviewers are more affective, so they tend to use easier way to express their feelings, such as posting pictures. In line with an adage going, a picture is worth a thousand words. Therefore, the more usage of pictures may reduce the usage of words in reviews. Thus, we believe tourist consumers tend to write shorter reviews and put forward the following hypothesis:

H3c: Compared to locals, tourists tend to write shorter reviews.

3. Research Methodology

3.1. Data

The review data are collected from a most popular restaurant review platform in China. Registered users can post online reviews and ratings for restaurants, disclose the average costs per person of their spending, rate the service quality, dining environment, and taste of the food. We collected the data of restaurant reviews for a matched set of restaurants from this platform. We first collected a restaurant-level data set by selecting 10 major and representative cities: Changchun, Changsha, Guangzhou, Guiyang, Haikou, Suzhou, Tianjin, Xi'an, Xiamen, and Zhengzhou. These cities range from the north to the south of China and are famous for their local food. We do not include the largest cities (Beijing, Shanghai and Shenzhen) because many "locals" living in these cities are immigrants themselves. For each city, we collected data on the 10 restaurants with the largest volumes of online reviews. We observe the complete history of all consumer reviews for all the restaurants. The data set contains time stamps and review contents (ratings and review texts), as well as the reviewers' profiles and restaurants' information. It is an efficient way for us to obtain review data by collecting data on restaurants with a large volume of reviews. However, this may induce the selection bias issue. To address this issue, we then obtained a reviewer-level data set by collecting a sample of reviews written by randomly selected 1500 users who contributed in the restaurant-level data set. For each of these reviewers, we acquired all their restaurant reviews posted on the platform and the information about those rated restaurants. At last, we obtained a reviewer-level data set involving nearly 40 thousand restaurants with large ranges of prices and popularities.

We conduct our main analysis at the reviewer-level and do robustness checks and mechanism analyses using both the reviewer- and restaurant-level data sets. As our purpose is to examine the influence of travel on consumers, we exclude the reviewers with reviews written only for local restaurants or only for nonlocal restaurants. At last, we obtain a total of 70,950 reviews written by 747 users for our main analysis. Table A2 in Appendix 3 provides the summary statistics of tourist and local consumers' reviewing behaviors separately. Given that this is just an aggregate view, we more deeply investigate the influence of travel on consumers' reviewing behavior by conducting formal econometric analyses in the next sections.

3.2. Variables and Measurement

Using the reviewer-level data set, we first conduct an ordered logit regression with robustness checks across different levels of restaurant prices, by restaurant chain property, by reviewer gender, and across different sizes of reviewers' residence cities, to identify the tourist bias in online ratings, and then we conduct mechanism analyses to uncover mechanisms underlying this phenomenon. Furthermore, we conduct a series of additional analyses controlling for time-variant restaurant quality and more mechanism analyses to identify the reason behind the bias based on the restaurant-level data set. We introduce variables included in our main analysis in this section.

Dependent Variable: Rating. *Rating* is an integer, ranging from 1 to 5, based on the five-star rating scale of the review platform. More stars indicate a more positive evaluation.

Independent Variable: Travel. *Travel* is a binary variable used to describe whether the rating is given for a restaurant experienced on a trip. It is determined by the location of the reviewed restaurant and the reviewer's location of residence. It is coded as a dummy variable, with 1 indicating that the two locations are different (i.e., the reviewer visited the restaurant as a tourist) and 0 meaning that they are the same (the restaurant is a local restaurant for the reviewer).

It is very easy to identify the location of a restaurant with the information provided by the platform. Reviewers' residence locations are reported at city level. In order to minimize the probability that our data set includes reviewers whose disclosed locations are mis-reported, we double check each reviewer's review history. If we find that the majority of the restaurants reviewed by a reviewer (especially during the last one-year period) are not in the city of his/her residence, we exclude this reviewer from our data set. We also drop the reviewers or restaurants whose locations are outside of mainland China.

Control Variables. We include a comprehensive set of restaurant-, reviewer-, and review-related covariates. They are: *Restaurant review volume*, measured by the volume of online reviews for a given restaurant; *Restaurant environment*, measured by the average rating for the restaurant environment given by consumers; *Restaurant price,* measured by the average cost per person for a dinner in the restaurant; *Reviewer age*, measured by the reviewer's age when s/he published the review, which is calculated as the time interval days between the review publishing date and the reviewer's disclosed birthday; *Review experience*, measured by the total number of restaurant reviews the reviewer had already published when s/he published the review; *Travel experience*, measured by the total number of reviews the reviewer had already published as a tourist when s/he published the review; *Review year FE*, measured by the year dummy when the review was published; *Review month FE,* measured by the month dummy when the review was published.

Detailed descriptions of all variables used in our main analysis are summarized in Table A3 in Appendix 4.

3.3. Econometric Models

As the dependent variable, online rating is an ordered and censored variable (an integer ranging from 1 to 5) that is not normally distributed. Following existing literature on online rating behavior (Huang et al. 2016, Sridhar and Srinivasan 2012), we employ the ordered logit model in our main analysis. To be more specific, we utilize random-effect ordered logit model to process our data by treating reviewer ID as panel variable and clustering standard errors according to reviewers. For other dependent variables used in the mechanism analyses, such as restaurant price and review length, we use linear models with controlling the fixed effects of reviewers.

4. Results

4.1. Main Analysis

4.1.1. Descriptive Statistics

Tables A4 and A5 in Appendix 5 report the descriptive statistics and correlation matrix of key variables in our main analysis, respectively. As shown in Table A4, the mean value of ratings is 4.017. This is consistent with other studies finding that online ratings tend to be positive. There exist large differences in restaurant-related variables (such as *Restaurant review volume* and *Restaurant price*).

The correlation matrix and variance inflation factor (VIF) values of the key variables in our main analysis are shown in Table A5. Correlations are generally small with the exception of the correlation between reviewers' review experience and travel experience (0.81). To formally test for multicollinearity, we calculated the VIF values for the independent variable and main control variables. Table A5 shows that the maximum VIF value is 3.59, implying no multicollinearity concerns (Mason and Perreault Jr 1991).

4.1.2. Regression Results

The final regression results for our main analysis are reported in Table 1. After controlling for the effects of control variables, we find that the coefficient is significantly positive (i.e., 0.126). To better interpret the meaning of this coefficient, we take the exponential form of it and obtain 1.134. It means that, given all other variables remain unchanged, the odds ratio increases to 1.134 if the reviewer is a tourist consumer. In other words, if a consumer experiences and rates the same restaurant both on travel and at home, the odds ratio (i.e., the ratio of the possibility s/he gives higher ratings on travel to the possibility s/he gives higher ratings at home) is 113.4/100. To better explain this finding, we also show the raw distribution of review ratings in Figure A2 in Appendix 6, through which we can know the baseline odds ratio.

In terms of control variables, *Restaurant review volume* has a positive parameter estimate, indicating that consumers rate popular restaurants higher. *Restaurant environment* has a positive estimate, suggesting that consumers tend to give higher ratings to restaurants with a better dining environment. Even after controlling for these quality-related variables, there is still a significant and substantial effect of *Travel* on ratings. As for the controls related to reviewers, *Review experience* is found to be negatively related to review ratings, implying that reviewers with richer review authoring experience are pickier.

Table 1. Regression Results for the Main Analysis

Variable	Model 1	Model 2
Travel		**0.126(0.045)*****
Restaurant price	0.040(0.030)	0.045(0.030)
Restaurant review volume	0.020(0.011)*	0.019(0.011)*

Restaurant environment	0.577(0.024)***	0.581(0.024)***
Reviewer age	0.489(0.352)	0.511(0.352)
Review experience	-0.216(0.054)***	-0.207(0.054)***
Travel experience	-0.036(0.060)	-0.046(0.059)
Intercept-5	3.497(3.285)	3.804(3.287)
Intercept-4	4.674(3.287)	4.981(3.289)
Intercept-3	6.733(3.288)**	7.041(3.289)**
Intercept-2	9.108(3.299)***	9.416(3.300)***
Review year FE	included	included
Review month FE	included	included
Number of Observations	70,950	70,950

Notes. Cluster robust standard errors (at the individual reviewer level) are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

We also conduct a marginal effect analysis to show the average marginal effects of travel on the probability of different ratings. The results are shown as Table A6 in Appendix 7. As we can see, the probability of providing a five-star rating by travelers is significantly higher than that by locals. At the same time, travelers' possibility of providing ratings lower than 5 stars is significantly lower than locals'.

4.2. Subgroup Analyses

According to the findings of the main analysis, restaurant- and reviewer-related characteristics also affect reviewers' ratings. Furthermore, several restaurant- and reviewer-related characteristics may also affect the relationship between travel and review ratings. Therefore, we conduct subgroup analyses to examine the robustness of the tourist bias and possible moderating effects. More specifically, we dig deeper and examine different types of restaurants by dividing restaurants into cheap and expensive ones, whether they belong to a chain or are independent. We also classify reviewers into male and female users and label the users to identify if they are from large or small cities.

4.2.1. Tourist Bias for Restaurants with Different Prices

The reviewer-level data set used in our main analysis contains 39,597 restaurants, whose prices range from 2 RMB to 1,799 RMB with a median value of 66 RMB. To further examine the tourist bias for restaurants with different qualities, we divide restaurants into two groups according to the median of restaurant prices: the expensive group with prices higher than or equal to 66 RMB and the cheap group with prices lower than 66 RMB. The differences in the main variables' effects on ratings between these two groups are reported in Table 2.

Table 2. Tourist Bias for Restaurants with Different Prices

Variable	All restaurants	Cheap restaurants	Expensive restaurants
Travel	**0.126(0.045)*****	**0.120(0.055)****	**0.129(0.049)*****
Restaurant price	0.045(0.030)	-0.176(0.037)***	0.410(0.048)***
Restaurant review volume	0.019(0.011)*	0.052(0.013)***	0.012(0.012)
Restaurant environment	0.581(0.024)***	0.611(0.036)***	0.522(0.030)***
Reviewer age	0.511(0.352)	0.819(0.366)**	0.299(0.291)
Review experience	-0.207(0.054)***	-0.279(0.068)***	-0.177(0.052)***
Travel experience	-0.046(0.059)	-0.067(0.074)	-0.026(0.056)
Intercept-5	3.804(3.287)	5.746(3.418)	3.287(2.721)
Intercept-4	4.981(3.289)	7.000(3.416)**	4.431(2.724)
Intercept-3	7.041(3.289)**	9.197(3.410)***	6.395(2.725)**
Intercept-2	9.416(3.300)***	11.690(3.420)***	8.733(2.734)***
Review year FE	included	included	included
Review month FE	included	included	included
Number of Observations	70,950	31,407	38,040

Notes. Clustered robust standard errors (at individual reviewer level) are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. 1,152 observations in cheap restaurant group and 351 observations in expensive restaurants are dropped as their authors just have local or travel reviews.

As we can see from Table 2, the upward tourist bias exists for both expensive and cheap restaurants, confirming the robustness of our main analysis. This result implies that consumers tend to provide higher ratings for restaurants visited during a trip no matter they are expensive or cheap. Besides, the upward tourist bias is more salient for expensive restaurants.

It is worth noting that *Restaurant price* exhibits a non-linear effect on ratings. Higher *Restaurant price* is associated with higher ratings for more expensive restaurants, but higher price is penalized in cheap restaurants.

4.2.2. Tourist Bias for Chain and Independent Restaurants

In this part, we classify restaurants into chain and independent restaurants to conduct a subgroup analysis. The differential effect of travel on ratings for chain and independent restaurants are shown in Table 3. The upward tourist bias holds for both chain and independent restaurants.

Table 3. Tourist Bias for Chain vs. Independent Restaurants

Variable	All restaurants	Chain restaurants	Independent restaurants
Travel	**0.126(0.045)*****	**0.231(0.081)*****	**0.091(0.045)****
Restaurant price	0.045(0.030)	0.026(0.047)	0.034(0.028)
Restaurant review volume	0.019(0.011)*	0.030(0.014)	0.019(0.011)*
Restaurant environment	0.581(0.024)***	0.725(0.052)***	0.569(0.025)***
Reviewer age	0.511(0.352)	0.730(0.422)*	0.528(0.304)*
Review experience	-0.207(0.054)***	-0.259(0.072)***	-0.211(0.053)***
Travel experience	-0.046(0.059)	-0.041(0.077)	-0.047(0.059)
Intercept-5	3.804(3.287)	7.006(3.983)	3.776(2.834)

Intercept-4	4.981(3.289)	8.098(3.982)**	4.991(2.835)
Intercept-3	7.041(3.289)**	10.239(3.977)***	7.048(2.835)***
Intercept-2	9.416(3.300)***	12.744(3.991)***	9.408(2.842)***
Review year FE	included	included	included
Review month FE	included	included	included
Number of Observations	70,950	14,795	54,000

Notes. Clustered robust standard errors (at individual reviewer level) are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. 1,920 observations in chain restaurant group and 235 observations in independent restaurant group are dropped as their authors just have local or travel reviews.

Since chain restaurants are highly consistent in their environment, taste, price, and food quality even in very different geographical locations, they offer an ideal way for us to remove unobserved heterogeneities that exist across different locations. Therefore, to robustly check the existence of tourist effect, we dig deeper into chain restaurants by conducting the following two analyses: (1) adding *Brand FE* as a control variable to control for the effects of chain brands for the analysis on chain restaurants; (2) re-conducting Analysis (1) with another data set in which every consumer visits the same chain restaurant both on travel and at home. The results are shown in Table A7 in Appendix 8. As shown in the results, the upward tourist bias still holds, confirming the robustness of our finding. Furthermore, we adopt fixed-effect ordered logit method to re-process the reviews for chain restaurants and those provided by consumers who visit the same chain restaurant both on travel and at home. The results can be found in Table A8 in Appendix 8, confirming the upward tourist bias as well.

4.2.3. Tourist Bias for Male and Female Reviewers

We also investigate the possible effect of reviewer gender on the relation between travel and ratings, and the results are shown in Table 4. As we can see from it, the upward tourist bias still holds for both male and female reviewers, also confirming the robustness of our main analysis. This finding implies that both male and female reviewers are prone to giving a higher rating for the restaurants visited during a trip.

Table 4. Tourist Bias for Reviewers with Different Genders

Variable	All reviewers	Male reviewers	Female reviewers
Travel	**0.126(0.045)*****	**0.170(0.077)****	**0.114(0.053)****
Restaurant price	0.045(0.030)	0.105(0.048)**	0.032(0.036)
Restaurant review volume	0.019(0.011)*	0.028(0.017)	0.016(0.013)
Restaurant environment	0.581(0.024)***	0.537(0.051)***	0.592(0.027)***
Reviewer age	0.511(0.352)	-0.080(0.594)	0.812(0.445)*
Review experience	-0.207(0.054)***	-0.155(0.133)	-0.223(0.059)***
Travel experience	-0.046(0.059)	0.024(0.160)	-0.066(0.061)

Intercept-5	3.804(3.287)	-1.270(5.621)	6.454(4.130)
Intercept-4	4.981(3.289)	-0.312(5.627)	7.695(4.133)
Intercept-3	7.041(3.289)**	1.929(5.649)	9.711(4.132)**
Intercept-2	9.416(3.300)***	4.274(5.662)	12.097(4.144)***
Review year FE	included	included	included
Review month FE	included	included	included
Number of Observations	70,950	14,388	56,562

Notes. Clustered robust standard errors (at individual reviewer level) are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

4.2.4. Tourist Bias for Reviewers from Cities of Different Sizes

Based on the demographic information of reviewers' locations, we can divide reviewers into two groups: reviewers from large cities and those from small cities. This part is similar to Kokkodis and Lappas (2020), but with one key difference: While Kokkodis and Lappas (2020) focus on the popularity disparity between cities, we examine how reviewers' residence city may influence the way they write ratings as tourists. Provincial capitals are classified as large cities, while others are classified as small ones. The effects of travel on reviewers for the two groups are summarized in Table 5. As shown in the table, reviewers from both large and small cities have the tendency to give higher ratings to restaurants when traveling.

Table 5. Tourist Bias for Reviewers from Cities of Different Sizes

Variable	All reviewers	Reviewers from large cities	Reviewers from small cities
Travel	**0.126(0.045)*****	**0.127(0.047)*****	**0.244(0.109)****
Restaurant price	0.045(0.030)	0.054(0.032)*	-0.116(0.040)**
Restaurant review volume	0.019(0.011)*	0.025(0.011)**	-0.043(0.029)
Restaurant environment	0.581(0.024)***	0.578(0.025)***	0.618(0.073)***
Reviewer age	0.511(0.352)	0.514(0.357)	0.124(1.642)
Review experience	-0.207(0.054)***	-0.213(0.055)***	-0.176(0.189)
Travel experience	-0.046(0.059)	-0.049(0.061)	0.052(0.176)
Intercept-5	3.804(3.287)	3.798(3.325)	0.274(15.390)
Intercept-4	4.981(3.289)	4.977(3.327)	1.432(15.374)
Intercept-3	7.041(3.289)**	7.056(3.326)**	3.250(15.474)
Intercept-2	9.416(3.300)***	9.427(3.339)***	5.757(15.422)
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	70,950	66,239	4,711

Notes. Clustered Robust standard errors (at individual reviewer level) are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

In addition to these subgroup analyses above, we use alternative methods including OLS, Ologit (ordered ologit) and random-effect ordered ologit after CEM (Coarsened Exact Matching) (Blackwell et al. 2009) to conduct robustness checks as well. These results can be found in Appendix 9. All of them support the reliability of our findings solidly.

4.3. Mechanism Analyses

The above analyses confirm the upward tourist bias. The mechanism behind this bias, however, is still unknown. Many factors may have an impact on a consumer's rating behavior. We examine the potential mechanisms behind the tourist bias from consumer perspective in this section. To be more specific, we aim to answer the following research questions: (1) Can the upward tourist bias be attributable to consumers' consumption pattern change? (2) Does the difference in the evaluation process between tourists and locals lead to the bias? (3) Do travelers and locals focus on different aspects of a restaurant? And will the differences lead to the upward tourist bias?

4.3.1. Consumers' Consumption Pattern Change Due to Traveling

To examine the relationship between travel and restaurant quality, and pin down reasons behind the upward tourist bias, we conduct an analysis on *Restaurant price*, *Restaurant environment*, and *Restaurant service*. The detailed variable measurements and descriptive statistics can be found in Appendix 10. The results are reported in Table 6. We can find that, in fact, consumers tend to visit restaurants with lower price and inferior environment and service when they are on a trip. Therefore, *H2a*, *H2b*, and *H2c* are all rejected, indicating that the upward tourist bias cannot be a result of consumers' consumption pattern change.

Table 6. Analysis of Consumers' Consumption Pattern Change

Variable	Model 1 (DV=*Restaurant price*)	Model 2 (DV=*Restaurant service*)	Model 3 (DV=*Restaurant environment*)
Travel	**-0.169(0.008)*****	**-0.114(0.006)*****	**-0.119(0.007)*****
Reviewer age	2.472(0.258)***	1.461(0.219)***	1.774(0.230)***
Review experience	-0.063(0.007)***	-0.031(0.006)***	-0.043(0.007)***
Travel experience	-0.027(0.007)***	-0.019(0.006)***	-0.017(0.006)***
Intercept	-18.815(2.356)***	-6.291(1.995)***	-8.999(2.097)***
Reviewer FE	included	included	included
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	70,950	70,950	70,950
F-statistic	19.94***	26.39***	22.27***
R^2	0.163	0.195	0.181

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

4.3.2. Consumers' Evaluation Process Change Due to Traveling

To better understand consumers' reviewing behavior considering their evaluation process behind ratings, we examine the effects of travel on review content, which is measured by *Review length*, *Review picture*, and *Cognitive content*. The detailed variable measurements and descriptive statistics can be found in Appendix 11.

The regression results are shown in Table 7. Tourist consumers write shorter reviews with fewer cognitive process words, and they are likely to include more pictures in a review as well. Different from the locals, the traveling consumers tend to express themselves using much easier and straightforward methods like posting pictures and writing fewer words. They also tend to write fewer cognitive words. Hence, *H3a*, *H3b*, and *H3c* are supported. These results indicate that tourist consumers are more emotional than locals, and this may induce them to provide higher ratings for restaurants experienced during a trip. This finding is also consistent with the findings of the topic analysis that tourist consumers pay more attention to peripheral factors (see Section 4.3.3 below).

Table 7. Analysis of Consumers' Evaluation Process Change

Variable	Model 1 (DV=*Review length*)	Model 2 (DV=*Picture number*)	Model 3 (DV=*Cognitive content*)
Travel	**-0.030(0.009)*****	**0.356(0.026)*****	**-0.003(0.001)*****
Restaurant price	0.262(0.006)***	0.849(0.017)***	-0.001(0.0004)***
Restaurant review volume	0.026(0.003)***	0.024(0.008)*	0.002(0.0002)***
Restaurant environment	0.029(0.006)***	0.348(0.018)***	-0.003(0.0005)***
Reviewer age	-0.580(0.291)*	4.768(0.911)***	0.095(0.024)***
Review experience	0.135(0.009)***	0.365(0.025)***	0.0004(0.0008)
Travel experience	0.052(0.009)***	0.196(0.023)***	-0.0004(0.0007)
Intercept	4.362(2.659)***	-44.611(8.282)***	-0.666(0.222)***
Reviewer FE	included	included	included
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	70,933	70,950	70,933
R^2	0.421	0.512	0.100

Notes. Robust standard errors are reported in parentheses. *: p<0.1; ***: p<0.01. The number of observations for Model 1 and Model 3 is smaller than that for Model 2 because 17 reviews just have ratings without review content.

4.3.3. Focus Change Due to Traveling

Tourists and locals may have very different focuses when evaluating a restaurant. We can observe their different focuses by conducting a topic analysis of the review texts. We use a standard LDA (Latent Dirichlet Allocation) model (Blei et al. 2003) to extract review topics. We remove non-Chinese words, special characters, and stop words from the reviews and run the model using 2-20 topics to determine the optimal number of topics. After considering topic meanings and coherence scores, which are treated as topic number selection criteria (Röder et al. 2015), we set the number to be four. The topics and the top words for each topic are reported in Table 8.

We can see topic differences between local and travel reviews from Table 8: Restaurant location, cooking method, and price are only discussed in local reviews, while restaurant environment and customer emotion are only discussed in travel reviews. Therefore, we can infer that the focuses of traveling consumers and local consumers are different. More specifically, local consumers are more realistic to care more about the location, price of the restaurant, and cooking method of food when evaluating restaurants, whereas traveling consumers express more emotions and care more about peripheral factors like restaurant environment and the service quality. The focus differences may impact consumers' rating behavior and thus be responsible for the upward tourist bias.

Table 8. Topics and Top Words for Each Topic in Travel vs. Local Reviews

Local reviews		Travel reviews	
Topic	Top words	Topic	Top words
Location	store, location, set up, storefront, road, building	Service	waiter, attentive, friendly, polite, queue, attitude, reservation
Cooking method	food, fry, steam, technique, traditional, flavor	Environment	environment, ambiance, interior, decoration, character
Price and service	buy, queue, bill, price, group-buying, waiter, reservation	Customer emotion	emotion, tired, pleased, disappointed, trust, look forward, surprised
Customer satisfaction	recommend, truly, unique, special, expectation	Customer satisfaction	recommend, truly, unique, special, expectation

5. Additional Analyses

In order to further examine the relationship between travel and review ratings, and explore the mechanisms behind the tourist bias, we conduct a series of additional restaurant-level analyses. To this end, we randomly selected 10 major cities: Changchun, Changsha, Guangzhou, Guiyang, Haikou, Suzhou, Tianjin, Xi'an, Xiamen, and Zhengzhou. For each city, we collected review data on 10 restaurants with the largest volumes of reviews. We observe the complete history of all consumer reviews for all the restaurants involved. The data set contains time stamps and review contents (ratings and review texts), as well as the reviewers' profiles and the restaurants' information.

5.1. Additional Robustness Checks

Average ratings used in our reviewer-level analyses cannot capture time-variant restaurant quality, which may have an impact on consumers' online rating behavior (Ho et al. 2017, Ma et al. 2014). To address this issue, we re-investigate the relationship between travel and ratings using a restaurant-level data set in this section. As we collected all historical reviews for each restaurant, we can control for time-variant restaurant quality using the average value of all prior ratings (i.e., *Prior_avg_rating*) for each focal rating. To reduce the influence of tourist rating bias, we only include ratings from the locals to calculate average ratings in this section. In addition, to better capture restaurant time-variant features, we take the observed restaurant price (*Prior_avg_price*), observed restaurant review volume (*Prior_review_volume*), both measured at the time of each focal rating, into account as well. The detailed descriptions and descriptive statistics of main variables can be found in Appendix 12.

Table 9. Regression Results for the Additional Robustness Check

Variable	Model 1	Model 2	Model 3
Travel	**0.045(0.015)****	**0.045(0.015)****	**0.045(0.015)****
Prior_avg_rating	0.765(0.056)***	0.622(0.040)***	0.679(0.046)***
Prior_avg_price	-0.013(0.046)	-0.038(0.040)	-0.025(0.043)
Prior_review_volume	0.025(0.012)**	0.033(0.011)***	0.035(0.011)***
Reviewer gender	-0.142(0.007)***	-0.142(0.007)***	-0.142(0.007)***
Reviewer followers	1.303(0.083)***	1.302(0.084)***	1.301(0.084)***
Reviewer activity	-0.231(0.005)***	-0.231(0.005)***	-0.231(0.005)***
Intercept-5	-1.720(0.801)	-1.698(0.470)	-2.050(0.781)**
Intercept-4	-0.868(0.801)	-0.845(0.470)	-1.197(0.782)
Intercept-3	0.598(0.801)	0.620(0.470)	0.268(0.782)
Intercept-2	2.224(0.801)**	2.246(0.470)***	1.894(0.781)**
Restaurant FE	included	included	included
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	451,139	451,027	451,117

Notes. Robust standard errors are clustered by restaurants, and they are reported in parentheses. **: $p < 0.05$; ***: $p < 0.01$. *Prior_avg_rating*, *Prior_avg_price*, and *Prior_review_volume* are time-varying variables, so they are not absorbed by *Restaurant FE*. *Prior_avg_rating*, *Prior_avg_price*, and *Prior_review_volume* are calculated based on all prior local reviews for Model 1, and they are calculated based on prior 6-month and prior 12-month local reviews for Model 2 and Model 3, respectively.

Ratings given years ago may be irrelevant to the current restaurant features, so we calculate average local ratings based on three time windows: all prior ratings, ratings provided in the past 6 months, and ratings written in the past 12 months. We report our additional robustness checks for the three time windows in Table 9. The positive relationship between travel and ratings still holds, which is consistent with our main analysis.

5.2. Additional Mechanism Analyses

The above analysis confirms the upward tourist bias using the restaurant-level data set. The mechanism behind the effect, however, can be further explored with this data set. In this section, we investigate consumers' rating behavior at city-, cuisine- and sub-dimensional rating-levels to examine whether travel destination, cuisine authenticity, and consumers' evaluation focus are responsible for the tourist bias.

5.2.1. City-Level Analysis

To find out whether travel destination is responsible for the tourist bias in consumers' rating behavior, we conduct comparisons between each pair of travel destinations (e.g., reviewers *from* Guangzhou *to* Tianjin vs. reviewers *from* Tianjin *to* Guangzhou). If travel destination is responsible for the tourist bias, then most of the travel pairs should have statistically significant difference in ratings.

After dropping reviews written by reviewers who are not from the selected 10 cities and those not written for a restaurant on travel, we obtain a total of 24,805 reviews from the restaurant-level data set. There are 45 travel pairs in total for the 10 cities, and we find that 35 out of 45 (nearly 80%) of the travel pairs do not have statistically different ratings.

The remaining 10 travel pairs that are statistically different in ratings are as follows: Guangzhou and Haikou (i.e., *from* Guangzhou *to* Haikou vs. *from* Haikou *to* Guangzhou); Guangzhou and Suzhou; Guangzhou and Changsha; Suzhou and Changsha; Suzhou and Xiamen; Suzhou and Changchun; Changsha and Xiamen; Changsha and Xi'an; Changsha and Zhengzhou; Xiamen and Xi'an. These differences can be mostly explained by the economic disparity between the pair of cities. There is no doubt that the economic circumstance of a city affects the online rating behavior of consumers from that city (Kokkodis and Lappas 2020). For example, consumers from richer cities may be pickier (Xu et al. 2019). City-level average wage can be used to measure a city's economic circumstance. Hence, we collected the average wage data for the 10 cities from 2005 to 2015 from the Census and Economic Information Center (CEIC) database (https://insights.ceicdata.com/) and calculated the mean values to obtain the 11-year overall average wage for each city. In the end, we obtain the overall average wages for the 10 cities (in RMB) as follows: Guangzhou (55,246), Tianjin (52,198), Suzhou (46,855), Xiamen (42,364), Changsha (41,821), Xi'an (38,607), Changchun (37,728), Guiyang (36,139), Haikou (35,663), and Zhengzhou (33,764). The overall average wage of Guangzhou is the highest among the 10 cities, and travelers *from* Guangzhou tend to give lower ratings than those traveling *to* Guangzhou. The same rating pattern exists for other city pairs, with exceptions of three pairs (Changsha and Xi'an, Xiamen and Suzhou, Changsha and Zhengzhou). The wage levels of the first two pairs are not significantly different, making it difficult to compare them directly only based on economic prospects. Changsha and Zhengzhou have significantly different wage levels, but our data set has only 31 observations on them, making the comparison not meaningful.

Since the majority of the travel pairs have no significant difference in ratings, we thus conclude that the tourist bias is not likely to be caused by the travel destination factor.

5.2.2. Cuisine-Level Analysis

When tourists visit a city famous for its authentic cuisine, it is possible that the higher ratings can be explained by cuisine authenticity rather than by other factors such as emotions or psychological distances. To investigate whether cuisine authenticity affects consumers' rating behavior, we focus on the ratings given by travelers and local residents for restaurants that specialize in local cuisines of that city. For example, we examine ratings for Cantonese restaurants located in Guangzhou (the provincial capital Guangzhou is widely regarded to have the most authentic Cantonese food). Seven out of the ten cities where the restaurants are located in the restaurant-level data set have famous local authentic cuisines. Tianjin, Xiamen, and Zhengzhou do not have widely agreed-upon local cuisines. Changchun is famous for Northeast cuisine, but none of the restaurants in the sample offers Northeast cuisine. In the end, we conduct a restaurant cuisine-level analysis for the remaining six cities, and the results are reported in Table 10.

Five out of six cuisines (Northwest cuisine of Xi'an, Hainan cuisine of Haikou, Hunan cuisine of Changsha, Jiangsu & Zhejiang cuisine of Suzhou, and Yunnan & Guizhou cuisine of Guiyang) do not support the cuisine authenticity hypothesis. For these five types of cuisines, local reviewers give higher ratings than traveling reviewers. Different from the other cuisines, Cantonese cuisine receives lower ratings from Guangzhou locals than from travelers. This is probably attributable to Cantonese people's famous pickiness for food. However, these comparisons are based on simple averages, we also conduct a regression analysis for authentic restaurants for cuisines except the Cantonese cuisine. The regression results are shown in Table A20 in Appendix 13. According to the regression results, there is no travel effect in this sample, implying that cuisine authenticity cannot be the reason for the tourist bias either.

Table 10. Restaurant Cuisine Based Comparison Results

Restaurant taste (Location)	Local review group I Mean (S. D.) *N*=Observation#	Traveler review group J Mean (S. D.) *N*=Observation#	Mean difference (I-J)	Difference *T*-test value
Cantonese cuisine (Guangzhou)	4.129(0.955) *N*=59,778	4.272(0.987) *N*=18,111	-0.143	**-17.476*****
Northwest cuisine (Xi'an)	4.414(0.893) *N*=23,232	4.288(1.006) *N*=25,096	0.126	**14.530*****
Hainan cuisine (Haikou)	4.344(0.863) *N*=221	4.163(1.040) *N*=1,026	0.181	**2.414****
Hunan cuisine (Changsha)	4.239(0.958) *N*=12,095	4.003(1.159) *N*=20,632	0.236	**18.923*****
Jiangsu & Zhejiang cuisine (Suzhou)	4.335(0.905) *N*=27,637	4.199(1.081) *N*=25,150	0.136	**15.702*****
Yunnan & Guizhou cuisine (Guiyang)	4.230(0.921) *N*=848	4.154(0.972) *N*=4,787	0.076	**2.114****

Note. **: $p < 0.05$; ***: $p < 0.01$.

5.2.3. Sub-dimensional Rating Analysis

In addition to overall ratings, the platform allows users to provide taste, environment, and service ratings for restaurants as well. We examine whether rating inflation exists for these sub-dimensions in this Section. The detailed results are shown in Tables 11-13. As we can see from the results, the upward tourist bias exists in taste and environment ratings but not in service ratings. This finding further indicates that consumers' evaluation focus is differential between tourists and locals, consistent with the finding of the topic analysis in Section 4.3.3.

Table 11. Regression Results for Taste Ratings

Variable	Model 1	Model 2	Model 3
Travel	**0.067(0.016)*****	**0.067(0.016)*****	**0.067(0.016)*****
Prior_taste_rating	0.781(0.066)***	0.681(0.048)***	0.771(0.055)***
Prior_avg_price	0.001(0.044)	-0.026(0.037)	-0.011(0.041)
Prior_review_volume	0.031(0.011)**	0.033(0.010)***	0.037(0.010)***
Reviewer gender	-0.106(0.007)***	-0.106(0.007)***	-0.106(0.007)***
Reviewer followers	1.221(0.081)***	1.220(0.081)***	1.217(0.081)***
Reviewer activity	-0.230(0.005)***	-0.230(0.005)***	-0.230(0.005)***

Intercept-5	-0.504(2.271)	-1.113(2.789)	-0.784(2.537)
Intercept-4	0.826(2.270)	0.216(2.789)	0.545(2.537)
Intercept-3	2.264(2.270)	1.655(2.789)	1.983(2.537)
Intercept-2	3.826(2.270)	3.217(2.789)	3.546(2.537)
Restaurant FE	included	included	included
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	451,198	451,149	451,194

Notes. Robust standard errors are clustered by restaurants and are reported in parentheses. **: p<0.05; ***: p<0.01. *Prior_taste_rating*, *Prior_avg_price*, and *Prior_review_volume* are calculated based on all prior local reviews for Model 1, and they are calculated based on prior 6-month and prior 12-month local reviews for Model 2 and Model 3, respectively.

Table 12. Regression Results for Environment Ratings

Variable	Model 1	Model 2	Model 3
Travel	**0.036(0.015)****	**0.035(0.015)****	**0.035(0.015)****
Prior_environment_rating	0.924(0.063)***	0.842(0.044)***	0.943(0.052)***
Prior_avg_price	0.027(0.040)	-0.007 (0.034)	0.001(0.035)
Prior_review_volume	-0.019(0.013)	-0.012(0.012)	0.000(0.012)
Reviewer gender	-0.160(0.008)***	-0.159(0.008)***	-0.159(0.008)***
Reviewer followers	1.298(0.084)***	1.295(0.084)***	1.289(0.008)***
Reviewer activity	-0.238(0.005)***	-0.238(0.005)***	-0.238(0.005)***
Intercept-5	-0.817(2.869)	-1.544(2.928)	-1.265(2.709)
Intercept-4	0.836(2.869)	0.111(2.928)	0.390(2.708)
Intercept-3	2.429(2.869)	1.706(2.928)	1.986(2.708)
Intercept-2	4.035(2.869)	3.312(2.928)	3.591(2.708)
Restaurant FE	included	included	included
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	451,198	451,149	451,194

Notes. Robust standard errors are clustered by restaurants and are reported in parentheses. **: p<0.05; ***: p<0.01. *Prior_environment_rating*, *Prior_avg_price*, and *Prior_review_volume* are calculated based on all prior local reviews for Model 1, and they are calculated based on prior 6-month and prior 12-month local reviews for Model 2 and Model 3, respectively.

Table 13. Regression Results for Service Ratings

Variable	Model 1	Model 2	Model 3
Travel	**0.018(0.014)**	**0.018(0.014)**	**0.017(0.014)**
Prior_service_rating	0.865(0.057)***	0.743(0.042)***	0.834(0.047)***
Prior_avg_price	0.040(0.044)	0.005(0.037)	0.022(0.040)
Prior_review_volume	-0.011(0.013)	0.000 (0.012)	0.008(0.013)
Reviewer gender	-0.153(0.008)***	-0.153(0.008)***	-0.153(0.008)***
Reviewer followers	0.932(0.077)***	0.930(0.077)***	0.928(0.077)***
Reviewer activity	-0.210(0.005)***	-0.211(0.005)***	-0.211(0.005)***
Intercept-5	0.025(5.092)	-0.807(5.466)	-0.501(4.915)
Intercept-4	1.344(5.092)	0.512(5.466)	0.819(4.915)
Intercept-3	2.720(5.092)	1.888(5.466)	2.195(4.915)
Intercept-2	4.137(5.092)	3.304(5.466)	3.611(4.915)
Restaurant FE	included	included	included
Review year FE	included	included	included
Review month FE	included	included	included
Number of observations	451,195	451,146	451,191

Notes. Robust standard errors are clustered by restaurants and are reported in parentheses. *: p<0.1; **: p<0.05; ***: p<0.01. *Prior_service_rating*, *Prior_avg_price*, and *Prior_review_volume* are calculated based on all prior local reviews for Model 1, and they are calculated based on prior 6-month and prior 12-month local reviews for Model 2 and Model 3, respectively.

5.3. Counterfactual Analysis

To examine the impact of tourist bias on the average rating of a restaurant, we conduct a counterfactual analysis. To be more specific, we first calculated the counterfactual rating probabilities for all tourist reviews by assuming they are local reviews, then we randomly selected 10 restaurants and compare the probability of actual 5-star ratings given by reviewers with that of 5-star ratings predicted by the counterfactual analysis for each restaurant. Through such an analysis, we can correct the bias caused by travel, which can be found in Table 14. As shown from this table, the probability of 5-star ratings for every restaurant decreases after correcting. The actual average ratings for all restaurants are larger than 4, so the smaller probability of 5-star ratings due to the counterfactual correcting induces the decrease of average rating of the restaurant. These results further support our main finding of the upward tourist bias and confirm its robustness.

Table 14. Restaurant-Level Rating Correcting Results

Restaurant No.	Actual rating Mean (S. D.) N = Number of observations	P_a	P_c Mean (S. D.)	P_a-P_c	Average rating change after correcting
Restaurant 88	4.108(0.911) N=6357	68.8%	67.2%(0.077)	1.6%***	Decrease
Restaurant 14	4.619(0.737) N=4,395	72.6%	70.4%(0.082)	2.2%***	Decrease
Restaurant 46	4.316(0.926) N=4,602	54.1%	53.5%(0.082)	0.6%***	Decrease
Restaurant 87	4.052(1.105) N=553	43.8%	41.8%(0.096)	2%***	Decrease
Restaurant 100	4.515(0.841) N=464	67.5%	66.2%(0.074)	1.3%***	Decrease
Restaurant 92	4.248(1.054) N=654	56.3%	53.5%(0.133)	2.8%***	Decrease
Restaurant 73	4.097(1.090) N=248	46.4%	43.9%(0.085)	2.5%***	Decrease
Restaurant 54	4.294(0.916) N=2,122	52.6%	51.8%(0.083)	0.8%**	Decrease
Restaurant 11	4.646(0.745) N=3,513	75.8%	74.5%(0.061)	1.3%***	Decrease
Restaurant 35	4.548(0.740) N=7,520	65.8%	65.5%(0.072)	0.3%***	Decrease

Note. **: $p < 0.05$; ***: $p < 0.01$. P_a: Probability of 5-star rating given by reviewers. P_c: Probability of 5-star rating predicted using counterfactual analysis. Reported correcting results are based on Model 1 in Table 9, whose *Prior_avg_rating*, *Prior_avg_price*, and *Prior_review_volume* are calculated based on all prior local reviews.

6. Conclusion with Discussions

6.1. Main Findings

The main purpose of this study is to investigate the effect of travel on consumers' rating behavior (i.e., the tourist bias) in the catering industry. More importantly, we aim to uncover the mechanism underlying the bias. Utilizing online restaurant reviews, we conduct a series of empirical analyses. We first perform an ordered logit regression followed by several robustness checks with subgroup analyses to confirm an upward tourist bias in online restaurant ratings. To identify factors inducing this bias, we also conduct reviewer-, restaurant-, cuisine- and city-level mechanism analyses. Related research questions and their corresponding main findings are summarized in Table A21 in Appendix 14.

This study obtains a series of interesting findings. First, we observe a significant difference between locals' and travelers' ratings, indicating the existence of tourist bias in online ratings. Specifically, travelers tend to give higher ratings than locals. In addition, this upward bias is persistent for both chain and independent restaurants across different restaurant price levels. The tourist bias also exists for both male and female reviewers from both large and small cities. The upward tourist bias also holds in a restaurant-level analysis while controlling for time-variant restaurant quality. Second, we examine possible mechanisms underlying the tourist bias. We find that many potential mechanisms such as consumption pattern change, cuisine authenticity, relative popularity of consumers' city of residence are not responsible for the tourist bias in online ratings. Instead, individuals' change in evaluation focus (from location, cooking, and price to service, environment, and emotions) and mood change (from cognitive to affective) can induce the tourist bias in ratings. Consistent with these changes, tourists' review content has more pictures, fewer words, and fewer cognitive words.

6.2. Implications

Our study has both theoretical and practical implications. From the theoretical angle, in line with studies on online rating biases, such as social influence bias (Lee et al. 2015, Moe and Trusov 2011, Wang et al. 2018), popularity bias (Goes et al. 2014), self-selection bias (Li and Hitt 2008), psychological distance bias (Huang et al. 2016), and popularity-difference bias (Kokkodis and Lappas 2020), our study finds a new form of bias related to travel in online restaurant ratings. After establishing the effect, we investigate potential mechanisms underlying the bias. We rule out travel destination, cuisine authenticity, and consumption pattern change due to travel as the source of the bias. Multiple results suggest that individuals' change in emotions leads to such a bias. In addition to reviewers' rating behavior, we also study the impact of travel on consumers' review content. We find that traveling consumers tend to provide reviews with fewer words, more pictures, and fewer cognitive content. According to the research literature in online review helpfulness, tourist bias may be a double-edged sword: Reviews with visual pictures provide rich and powerful information to readers, while shorter review length can weaken review helpfulness (Mudambi and Schuff 2010).

In addition to the statistical significance of the upward tourist bias, this bias is also economically important. As we discuss earlier, tourist consumers are at least 13.4% more likely than local consumers to provide a higher restaurant rating. This finding has important implications for platform managers, system developers, product and service providers, as well as consumers.

For online review platform managers, our study suggests that in order to provide useful product and service evaluations, it is important to distinguish between reviews submitted by locals and those by tourists. Considering the tourist bias, system developers should label reviewer types (travel or local) or allow visitors to sort reviews according to this dimension. Based on our results, tourist consumers not only give higher ratings but also tend to post more pictures. This can ultimately contribute to the quality and stickiness of the platform. Therefore, it is advisable for platform managers to encourage travelers to write online reviews. Our results also show that travelers tend to write shorter reviews with fewer cognitive words. Prior work, however, reports that short reviews are perceived as being less helpful (Mudambi and Schuff 2010). Thus, to improve the quality of online reviews, review platforms should not only improve the volume of traveler reviews but also increase the helpfulness by encouraging users to write longer reviews with more subjective words. Review platforms are advised to recommend online reviews given by tourists and locals to tourists and locals separately.

Our study also offers useful insights to product and service providers. As our findings suggest that travel may inflate ratings, product and service providers should react to different types of reviews differently. It is important to understand that the locals are after convenient location, good taste, and lower price, but the tourists are attracted by friendly service, dining environment and ways to express their emotions. Meeting the different needs of different types of consumers not only helps the providers to improve their WOM ratings but also ultimately improves their service quality and long-term reputation.

This study also has implications for consumers. Local consumers certainly do not want to be biased by tourists' ratings; hence they should pay attention to reviewers' location information while reading restaurant reviews and mainly trust reviews written by locals. Tourists should also take reviewers' location into consideration when they search for the most relevant reviews. Which type of reviews are more important to tourist consumers depends on their travel style. Knowing reviewer types will help tourists to make a conscious choice of behaving like the locals or following the crowd of the tourists.

6.3. Limitations and Future Work

This study still has several limitations to note. First, due to API limitations, we had to collect our reviewer data and restaurant data separately, which makes us unable to control for the time-variant features of restaurants and reviewers at the same time. A unified data set that contains complete historical reviews for both reviewers and restaurants would be ideal. Second, the setting is in the context of online reviews for restaurants in China. While this setting offers the advantage to conduct a cuisine-level analysis, it will be interesting to see how these effects can be generalized to other geographical areas. Third, in view of the double-edged sword effect of travel on online review helpfulness mentioned earlier, future research may investigate how review helpfulness can be further examined if the travelers and locals are considered separately.

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