Title
The Economic Value of Online Reviews

Journal
Marketing Science, 34(5)

ISSN
0732-2399

Authors
Wu, Chunhua
Che, Hai
Chan, Tat Y
et al.

Publication Date
2015-09-01

DOI
10.1287/mksc.2015.0926

Peer reviewed

Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

The Economic Value of Online Reviews

Chunhua Wu, Hai Che, Tat Y. Chan, Xianghua Lu

MARKETING SCIENCE
Vol. 34, No. 5, September–October 2015, pp. 739–754
ISSN 0732-2399 (print) | ISSN 1526-548X (online)

http://dx.doi.org/10.1287/mksc.2015.0926

The Economic Value of Online Reviews

Chunhua Wu
Sauder School of Business, University of British Columbia, Vancouver, British Columbia V6T 1Z2, Canada, chunhua.wu@sauder.ubc.ca

Hai Che
Kelley School of Business, Indiana University, Bloomington, Indiana 47405, haiche@indiana.edu

Tat Y. Chan
Olin Business School, Washington University in St. Louis, St. Louis, Missouri 63130, chan@wustl.edu

Xianghua Lu
School of Management, Fudan University, 200433 Shanghai, China, lxhua@fudan.edu.cn

This paper investigates the economic value of online reviews for consumers and restaurants. We use a data set from Dianping.com, a leading Chinese website providing user-generated reviews, to study how consumers learn, from reading online reviews, the quality and cost of restaurant dining. We propose a learning model with three novel features: (1) different reviews offer different informational value to different types of consumers; (2) consumers learn their own preferences, and not the distribution of preferences among the entire population, for multiple product attributes; and (3) consumers update not only the expectation but also the variance of their preferences. Based on estimation results, we conduct a series of counterfactual experiments and find that the value from Dianping is about 7 CNY for each user, and about 8.6 CNY from each user for the reviewed restaurants in this study. The majority of the value comes from reviews on restaurant quality, and contextual comments are more valuable than numerical ratings in reviews.

Keywords: online reviews; user-generated content; consumer choice under uncertainty; learning; economic value to consumer and firm

History: Received: December 12, 2012; accepted: March 18, 2015. Preyas Desai served as the editor-in-chief and Harald van Heerde served as associate editor for this article.

1. Introduction

With the prevalence of Internet use, online reviews have become an important source of word-of-mouth. A survey by AC Nielsen found that consumers trust opinions from friends the most. Online consumer reviews are second.[1] Companies such as Yelp and Angie's List, specializing in online reviews of restaurants, doctors, and other local businesses, provide millions of reviews on their websites and attract millions of visits every day.[2] The success of these companies is built on their competency in providing consumers with valuable information and attracting website visits, which is the key to generating revenue.

Our primary goal here is to measure the economic value of online reviews for consumers and firms. Furthermore, we investigate how review websites can improve the economic value of reviews. Review websites typically supplement each review with additional information. In addition to giving ratings based on a predetermined scale, reviewers are often requested to provide detailed comments on their experience. Further information related to individual reviewers (e.g., a reviewer's status based on past contribution) and reviews (e.g., how many users find this review useful) are also provided. This study helps to address two managerial questions: (1) How does the information on reviewer and review characteristics enhance the economic value of reviews? Answering this question is important for review websites to provide better features that are useful for consumers; (2) How do online reviews affect consumers' restaurant choice and thus restaurants' revenue? Answering this question helps restaurant owners to understand the impact of online reviews on their business, which can affect their advertising and promotion decisions at review websites.

To achieve these goals, we use data from Dianping.com, a leading Chinese consumer review website, to examine how a consumer learns about multiple

[1] http://blog.nielsen.com/nielsenwire/media entertainment/consumer-trust-in-online-social-and-mobile-advertising-grows/, accessed April 15, 2012.

[2] For example, in 2011 Yelp featured more than 22 million reviews of local businesses and claimed to have more than 61 million unique visitors per month in the latest quarter. Its current market cap is $1.2 billion.

attributes, such as the quality and cost of restaurant dining, by reading online reviews, and how this learning impacts her restaurant choice. With these results, we conduct counterfactual experiments to study how the consumer's choice would change under different scenarios of information provision from reviews. Based on the outcomes we then measure the value of online reviews.

We propose a new consumer learning model that is embedded in the consumer restaurant choice model. The learning model has several novel features. First, standard Bayesian learning models widely adopted in the marketing literature (e.g., Roberts and Urban 1988, Erdem and Keane 1996) implicitly assume that every review is equally informative. Thus, they do not allow for some reviews to be more informative than others. In our proposed model, we allow a consumer to differentiate reviews in terms of informational value, depending on how these reviews are perceived to correlate with her own taste. Second, with such a correlation, online reviews can help the consumer to infer her own preference for the reviewed business. Consequently, online reviews can be more valuable to consumers than is implied by standard learning models. Whereas extant learning models do not differentiate between the information value of reviews written by different reviewers (we call this "undifferentiated learning"), we propose "differentiated learning" where consumers do differentiate between reviewers and learn based on perceived taste correlations with the reviewers. Third, there can be a large diversity in reviews even for the same product or service. Consumers may perceive it as a risk when reviews are diverse. Standard learning models typically assume that the only target of learning is the average evaluation in the consumer population. Our proposed model allows consumers to also learn and update the variance in online reviews, enabling us to more correctly infer how the diversity of reviews drives the restaurant choice.

Additionally, online reviews provide consumers information on multiple product or service attributes, the measurements of which may be different in nature. The cost of dining in a restaurant, for example, can be objectively measured in terms of dollar amount; the quality of the restaurant, on the other hand, is subjectively evaluated by reviewers. Furthermore, from a consumer's viewpoint, the correlation of her and reviewers' quality preferences may be different from the correlation of her and reviewers' spending in a restaurant. To use the information effectively, consumers may adopt different learning strategies for different attributes when reading online reviews. We test whether these differences exist when applying our proposed learning model to data.

Identification of the learning mechanisms proposed in this research relies on the detailed nature of our data. The key advantage of using the data from Dianping is that we observe consumers' dining choices after reading reviews. This is critical for identification of the impact of user reviews on consumer choices. In addition, we observe for each review not only the ratings but also the comments written by the reviewer. This information component is critical for identification of the learning of variance in review evaluations. We also collect detailed information displayed in each review about the review and reviewer characteristics. When combined with restaurant choice data, we can infer how reviews from different reviewers influence the choices of different types of consumers in different ways. By assuming that reviews are unbiased and consumers can rationally infer their taste correlation with reviewers, we can use model estimation results to conduct counterfactual experiments and measure the economic value of online reviews.

Our estimation results show that when reading reviews consumers simultaneously adopt two learning mechanisms: For quality, reviews are given different weights in the learning process. Based on that, consumers learn their own preferences ("differentiated" learning). For cost, reviews carry the same weight in learning, and consumers only learn the overall distribution of evaluations ("undifferentiated" learning). When learning about quality, the information on the status of a reviewer, the length of the reviewer's comment(s), and the number of helpful votes the review receives all significantly impact a consumer's perception of how the review is correlated with her own taste. Consumers also perceive reviewers' comments as more informative than ratings. Finally, we find that the learning of variance in quality evaluations significantly impacts consumers' restaurant choices.

Based on the estimation results, we conduct counterfactual experiments to quantify the economic value of online reviews for consumers and restaurants. The economic value of reviews for consumers is based on the increment in utility from making a better choice after reading the reviews. We convert the increment to the dollar value by calculating how much of a cost decrease the increment in utility corresponds to. The economic value of reviews for firms is the incremental profit from visitors who have been attracted by the reviews. We construct our measurement based on the difference between the decisions consumers would make under different scenarios of information provision. Overall, reviews from Dianping increase the value for a consumer by 6.7 CNY (Chinese yuan). The majority of the value comes from information on restaurant quality. We also find that reviewers' comments are much more valuable for consumers than ratings. The information on reviewers' star status is also important in enhancing the value. For restaurants, online reviews increase the probability of consumer visits, and thus increase their profit by 8.6 CNY per consumer who visits Dianping. The information on restaurant quality again contributes most to this profit increase.

1.1. Related Literature

We contribute to the stream of literature on the effect of word-of-mouth and consumer reviews. Chevalier and Mayzlin (2006) show that, whereas positive reviews will increase sales, the impact from a negative review has a larger magnitude. Moe and Trusov (2011) study the dynamics of online product reviews and find that future reviews are affected by currently posted reviews. Most of these studies use macro-level or aggregate data; Zhao et al. (2012) is an exception. The authors study the effect of online product reviews on book purchases, and model how consumers' perception of the credibility of product reviews evolves over time. Our study uses individual level data. We also allow consumers to learn over multiple attributes (cost and quality), instead of single-dimensional learning as in Zhao et al. (2012).

Our study is in the stream of the empirical literature of learning (for a survey of these papers see Ching et al. 2013). Existing learning models assume that consumers learn and update the mean of information signals in a Bayesian framework. We also model the updating process for the variance of signals, which is consistent with the literature of the Kalman filter (Kalman 1960) and dynamic linear models (e.g., Harrison and Stevens 1976). Our differentiated learning mechanism shares some similarities with Erdem (1998), who considers a model whereby priors are correlated across umbrella brands, and finds evidence that consumers learn via experiences across categories for umbrella brands. This modeling framework was recently applied by Szymanowski and Gijsbrechts (2012) in the study of cross-learning in private labels. Che et al. (2015) develop a different correlated learning model by allowing consumer experience of a particular brand size to provide quality signals for other brand sizes. By contrast to these applications, our model assumes that consumers learn from the correlation of evaluations with individual reviewers.

Previous economics and marketing literature has also studied the consumer learning process of multiple product or service attributes. Crawford and Shum (2005) and Chan and Hamilton (2006) model the impact and learning of treatment effectiveness and side effects using pharmaceutical treatment outcomes. Chan et al. (2013) model the physician learning of treatment effectiveness and side effects of different drugs in the ED category. Erdem et al. (2008) model the quality signaling role of price in the content of frequently purchased goods. Our paper differs from the above studies by proposing new learning mechanisms that can apply in the context of online reviews.

The rest of the paper is organized in several parts. In §2, we describe the data and provide some reduced-form data evidence to help motivate the proposed model. In §3, we present our empirical model that studies consumer learning about quality and cost from online reviews. We then discuss the model specification, selection, and identification issues, and present the estimation results in §4. In §5, we show the counterfactual experiment results in which we measure the economic value of online reviews for consumers and restaurants. We conclude the paper in §6 and suggest directions for future research.

2. Data and Reduced-Form Analysis

Review websites such as Yelp.com and Dianping.com typically allow users to start searching for local business reviews at the home page based on specific criteria, such as geographical location, user rating or price. A list of search results (i.e., businesses) is then displayed in an ascending or descending order, based on the filtering criterion a user chooses. General information about reviews, such as the average rating and the number of reviews that a business receives, will show in the search results page. If interested in a particular business, users can click from the search result link into the business review pages to read more detailed comments, ratings, pictures, etc., available in each review provided by other users who are consumers themselves. Reviews are typically displayed based on posting time, but users can also sort reviews by other criteria such as geographical distance, price or rating. Some websites such as Amazon.com display the most favorable and the most critical reviews side by side on the same page, probably because users care about the divergence of reviewers' opinions. Reading these reviews allows users to obtain better information on business product or service attributes before making their own purchase decisions.

2.1. Online Reviews at Dianping.com

Because our data is collected from Dianping.com, we focus on discussing online reviews from that website. Founded in 2003, Dianping has become the largest independent consumer review website in China. The revenue of Dianping.com[3] comes from three sources:

[3] Dianping covers 2,000 cities in China, with more than 1 million local businesses on its website. It has over 20 million ratings and business reviews, attracting over 30 million active visitors every month. In addition to restaurants, it provides reviews for other consumer-service oriented businesses, such as hair salons, grocery stores, and golf courses. Focusing on affluent urban, white-collar

(1) selling display and keyword search advertising; (2) offering online coupons for participating restaurants in return for an advertising fee; and (3) offering discount card and group-buying to members and getting a share from participating restaurants if the discount card or group buying is used/purchased. A larger number of visits that Dianping can attract will increase the willingness-to-pay of restaurants for advertising and participating in promotional activities. To attract visits, however, Dianping needs to provide users with value from reading reviews. For more details, see an interview with Tao Zhang, the CEO of Dianping, in Bye (2009).

When a user logs into Dianping, she can search for a restaurant based on cuisine types or geographical areas, or directly search by keywords (e.g., restaurant, cuisine or dish). She will then find a list of restaurants. At the top of the list are three or four featured restaurants with sponsored links. The rest of the restaurants are presented in order of overall rating. After the user clicks on a restaurant link, reviews are shown, by default, in the order of descending posting time. A restaurant review typically reports several ratings on a scale from 1 (worst) to 5 (best), for the taste of food, ambience, and service. Here we use the average of the three attribute ratings as the measurement for quality rating[4] which is highly correlated with each rating item, with the mean correlation coefficient of 0.80. Below the posted ratings, users can find a contextual script (content) that provides comment on what the reviewer likes or dislikes about the restaurant. Dianping restricts the length of content to be between 50 and 1,000 Chinese characters. We measure the sentiment of each review content, which represents the degree of negativity or positivity from −1 (extremely negative) to 1 (extremely positive). To construct this measurement, we first translate the reviews from Chinese to English using Google Translate. We then use a commercial product, AlchemyAPI, to extract keywords. The sentiment is calculated from the extracted keywords.[5] A limitation of the measurement is that other contexts (e.g., recommendation of special dishes) are not taken into account.

Reviewers also provide information on the average spending per person. The spending is related to food prices, as well as how much a consumer uses. There can be a large variation in the reported spending across reviewers. Reviewers can submit pictures of restaurants and dishes. Furthermore, users can vote "helpful" if they find the review informative and useful. The number of helpful votes is shown under each review. Finally, every website member is assigned a "star" status by the website. This status is also displayed next to the reviewer's user name. There are eight levels, from "new" to "diamond." These are determined by the number of reviews a member has contributed and the number of "helpful votes" she has received for her reviews. A higher star indicates that the reviewer is more experienced and more likely to be perceived as an expert.

2.2. Sample Construction

Our data period is from December 2007 to March 2008. The data set consists of information after a user clicks into the review pages of restaurants from the search results page. There are two main parts: (1) user browsing, and (2) user dining choices, of restaurants in Shanghai, which is the largest city in China and the birthplace of Dianping. We focus on restaurants of one specific type of cuisine, "hot pot,"[6] to minimize biases due to differences in consumer tastes among cuisines. We merge the data sets to link consumers' browsing activities with restaurant choices. To capture the consumer choice set, we construct browsing sessions that include sequential visits to different restaurant pages from the same user, if the time interval between two sequential visits is fewer than 60 minutes.[7] Restaurants whose Web pages are visited within a browsing session are considered to be in the choice set. We then verify whether a user visits any of the restaurants in the next seven days. Restaurant visits are inferred from the usage of her discount card. Dianping's discount cards can be used in 450 restaurants in Shanghai during the sample period. The discount is usually 10% to 30% of the dining cost, which is a significant savings for any consumer. Also, using the discount card helps to accumulate reward points that can be used to redeem gifts. Therefore, the proportion of users who visit a restaurant without taking advantage of the discount should be small.

To reduce the computational burden in model estimation, we identify the seven most popular "hot pot" restaurants that participate in Dianping's reward program, which allow consumers to use the discount

consumers, its business is growing fast. Most of its users are in major and fast growing cities such as Beijing, Shanghai, and Guangzhou. Whereas Chinese Internet users skew younger, with half under the age of 24, Dianping's user base is older; most visitors are between 20 and 35 years old. The company's 2010 profit was CNY 200 million (US $30.6 million).

[4] Our model can be extended to include learning for each attribute. However, the high correlations of the three ratings create difficulty in identification in model estimation.

[5] We also do this manually for some reviews and find our measurement to be highly consistent with the above procedure.

[6] Hot pot (Chinese: 火鍋; pinyin: huǒ guō), sometimes also called the Chinese fondue or steamboat, refers to several East Asian varieties of stew, consisting of a simmering metal pot of stock at the center of the dining table.

[7] We obtain similar Web sessions when using 30 minutes or 120 minutes for the interval.

Table 1 Summary Statistics of the Focal Restaurants

Chain ID	Store ID	Number of reviews	Conversion rate	Review rating		Review content		Average cost (100 CNY)		Review length		Helpful votes	
				Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.	Mean	S.d.
A	1	636	0.16	2.13	0.68	0.10	0.15	0.82	0.18	239	202	3.1	7.6
	2	626	0.18	2.14	0.70	0.11	0.16	0.84	0.18	238	200	3.6	6.9
	3	413	0.17	1.97	0.66	0.08	0.17	0.81	0.17	212	187	3.0	6.9
B	4	526	0.14	1.99	0.66	0.11	0.17	0.84	0.19	312	304	8.4	19.7
	5	111	0.14	1.95	0.65	0.11	0.16	0.88	0.19	431	388	13.5	26.6
C	6	446	0.13	2.43	0.62	0.10	0.15	0.80	0.18	345	287	11.4	26.8
D	7	601	0.13	2.02	0.64	0.12	0.15	0.82	0.17	360	338	9.6	20.5

card. Among the 40 participating hot pot restaurants in our sample period, these seven account for 41% of clicks and 38% of revenue among Dianping members. We select browsing sessions that visit at least one of the Web pages from the seven restaurants for this study. This gives us a sample of 8,918 browsing sessions from 5,084 unique users. Table 1 provides some summary statistics for the seven hot pot restaurants in the sample. Restaurants 1, 2, and 3 that belong to Chain A have more reviews and a higher conversion rate, i.e., the probability of users dining in the restaurant after reading reviews. Yet reviewers tend to give shorter comments and their reviews receive fewer "helpful votes." The restaurants are not too different in terms of average ratings, content, and reported costs per person.

Table 2 summarizes browsing sessions and restaurant visits in data. We group all participating restaurants other than the seven focal restaurants as "outside restaurants." We also compare the statistics for "new visitors" and "returned visitors." A returned visitor is defined as a user who in the previous 30 days visited one of the seven restaurants and then read reviews for the visited restaurant in the current browsing session. On average users read reviews for four to five restaurants, indicating that they often compare restaurants based on reviews. The table shows that 15% of browsing sessions would result in dining in one of the seven focal restaurants. The conversion rate for all other restaurants is only 4.3%. The majority of users, however, chose not to visit any of the reviewed restaurants.

Table 2 Summary Statistics of the Web Sessions

	Number of sessions	Average number of outside restaurants viewed	Number choosing one of the seven restaurants	Number choosing an outside restaurant	Number choosing not going
Session of new visitors	7,729	3.8	1,209	349	6,171
Session of returned visitors	1,189	3.2	150	32	1,007

2.3. A Reduced-Form Regression Analysis

Because the value of online reviews will be inferred from restaurant choices, we want to first make sure from the data that reading online reviews has an impact on restaurant choice. We use a Multinomial Logit (MNL) regression to investigate the relationship. We group restaurants other than the seven focal restaurants as the option of outside restaurants, and also allow for a "no choice" option. Every user has an own choice set based on her browsing. The utility of going to one of the focal restaurants in the choice set is $u_{ij} = \bar{u}_{ij} + \epsilon_{ij}$, where $\bar{u}_{ij}$ is a linear function of multiple variables constructed from the reviews that user i reads (see Table 3). The utility of going to outside restaurants is defined as $U_{io} = \ln(\sum_l \exp(V_{il})) + \epsilon_{io}$, where $V_{il} = \alpha_0 + \alpha_1 R_{il}$ and R_{il} is the average rating of a restaurant, based on the reviews that the user reads, in the set of outside restaurants.[8] We use this inclusive value function construct as a proxy for the expected maximum value of the restaurants. Finally, the utility of not going to any of the browsed restaurants is $u_{in} = \epsilon_{in}$. We assume that all error terms follow an i.i.d. Type-I extreme value distribution.

Table 3 reports the regression results. We find a significantly positive effect from the sentiment in reviewers' comments (see the coefficient for "average content") and a negative effect from the average reported price ("average price"). Whereas the estimate for the average rating is insignificant, the variance of ratings significantly reduces the choice, indicating that consumers are averse to the risk of quality. This motivates our modeling of how consumers learn the variance in reviewers' evaluations from online reviews, as we will discuss in §3.

[8] We collect only the ratings measurement for outside restaurants. Although there are hundreds of restaurants in this group, the time and effort required to construct measures for other variables (e.g., translating comments) make it infeasible for us to study their effects.

Table 3 Multinominal Logistic Regression on Choosing a Restaurant

	Logit model	
	Estimate	t-value
Store dummies	Not reported	Not reported
Average rating	0.29	0.90
Variance of rating	**−1.94**	−2.81
Average content	**1.62**	2.19
Variance of content	−4.06	−1.60
Average cost	**−1.37**	−2.00
Variance of cost	1.18	0.89
Average reviewer star	**−0.17**	−1.93
Variance reviewer star	−0.01	−0.27
Average helpful votes	−0.02	−0.15
Variance of helpful votes	**0.31**	3.27
Average length of comment	**−0.39**	−2.18
Variance of length of comment	−0.23	−1.43
Outside restaurants intercept (α_0)	**−3.94**	−34.79
Ratings for outside restaurants (α_1)	**0.50**	11.02
Log-likelihood	−5,183.54	

Note. Bold numbers represent significance at 0.05 level.

Although one may consider star reviewers as opinion leaders, results show a significant negative effect of the average of reviewers' star status on users' restaurant choices. Although the average number of helpful votes does not increase the choice probability, its variance does. The average length of review comments has a negative effect. Finally, for outside restaurants, the positive estimate for average ratings indicates that more consumers will choose this option if their ratings are high. Overall, these results suggest that online reviews have a significant effect on consumers' restaurant choice.

3. The Model

In this section we formally introduce our proposed model. Because we do not have data on how a user starts searching at Dianping, the model focuses on consumer learning and restaurant choice after the user clicks into the restaurants review pages. Furthermore, to simplify the analysis, we treat different browsing sessions of the same user as independent, assuming that there are no information spillovers across browsing sessions, and that the choice set of one session is not influenced by earlier sessions. We acknowledge these as restrictions of this study.

For a browsing session i in our sample, the user has a choice set S_i, which includes one or more of the seven focal restaurants and possibly other restaurants. The choice set is assumed to be exogenously given. For each restaurant $j \in S_i$, there are multiple attributes, represented by a vector variable $\mathbf{A}_{ij}$ (in our context it includes the quality Q_{ij} and the reported dining cost C_{ij}) that will influence the user's consumption utility. We assume that these are individual specific because each user may have their own preferences for food and services and choice of what dishes to order. For an attribute A_{ij} (e.g., quality), the user has a prior expectation $E(A_{ij})$, and a prior uncertainty, which is captured by the variance $\mathrm{Var}(A_{ij})$. At the stage of information search, the user reads K_j reviews for every restaurant j in the choice set, and altogether $K = \sum_{j \in S_i} K_j$ reviews. In all restaurant review pages, reviews are sorted by posting time by default. We assume that the reviews the user reads follow such order.[9] All of these reviews provide her the information set I_K, which is treated as exogenous in the model. Based on I_K, the consumer will update her beliefs, forming the updated expectation $E[A_{ij} \mid I_K]$ and the uncertainty $\mathrm{Var}[A_{ij} \mid I_K]$. The consumer will then use these updated beliefs to form her expected utility for dining at each of the restaurants in the choice set, and go to the one with the highest expected utility, if it is higher than the utility of the no choice option.

3.1. Consumer Utility

The expected (indirect) utility function of visiting restaurant j, one of the seven focal restaurants, in the choice set, is specified as the following:

$$\begin{aligned}E[U_{ij} \mid I_K] &= \alpha_{ij} + w_i^Q\{E[Q_{ij} \mid I_K] + \gamma_i^Q E[Q_{ij}^2 \mid I_K]\}\\ &\quad + w_i^C E[C_{ij} \mid I_K] + \epsilon_{ij}\\ &= \alpha_{ij} + w_i^Q\{E[Q_{ij} \mid I_K] + \gamma_i^Q (E[Q_{ij} \mid I_K])^2\\ &\quad + \gamma_i^Q \mathrm{Var}[Q_{ij} \mid I_K]\} + w_i^C E[C_{ij} \mid I_K] + \epsilon_{ij}. \qquad (1)\end{aligned}$$ [10]

The utility parameters include α_{ij}, measuring the user's intrinsic preference for the restaurant; w_i^Q and w_i^C, representing the utility weights of quality and cost; and γ_i^Q, the risk preference for quality.[11] The error term ϵ_{ij} is the user's preferences unknown to researchers and is assumed to follow the standard

[9] Although we do not have detailed data on whether a user sorted reviews, conversation with Dianping managers reveal that most consumers use the default order.

[10] We choose such specification because it is derived from consumer maximization from a direct utility function under linear budget constraint, assuming discrete restaurant choice. We also test another specification with a quadratic term for the cost. The estimated coefficient for the quadratic term is statistically insignificant, and other estimates are similar to the current specification.

[11] Under this specification, the user is risk-neutral for cost, but risk-averse for quality if r^Q is negative. Her absolute risk aversion and relative risk aversion remain constant as her wealth or budget changes, and are an increasing function of the expected quality. One of the potential issues for the quadratic functional form is that there is a satiation point, where the marginal utility of quality becomes negative when the expected quality is larger than this level. One should not use this model to predict consumers' choice when quality is out of the data range.

Type-I extreme value distribution. The probability that she chooses restaurant j therefore is

$$\theta_{ij} = \frac{\exp(\bar{U}_{ij}(I_K))}{1 + \exp(\bar{U}_{io}) + \sum_{j' \in S_i} \exp(\bar{U}_{ij'}(I_K))}, \tag{2}$$

where S_i is the user's choice set that may include multiple focal restaurants, and $\bar{U}_{ij}(I_K)$ is the deterministic part in Equation (1) without ϵ_{ij}. Other than the inside restaurants in S_i, the user can also choose an outside restaurant. This utility is captured by $\bar{U}_{io} = \ln[\sum_l \exp(V_{il})]$ as a reduced-form proxy for the expected maximum utility of visiting outside restaurants, as we specified in the last section; and not to visit any of the reviewed restaurants, which utility is captured in "1" in the denominator.

3.2. Consumer Learning from Reviews

We assume that consumers learn restaurant attributes, including the quality and cost, from reading reviews. Dining cost depends on what dishes are ordered, which depends on a person's taste and dining occasions. In our data, different reviewers report different levels of spending (cost). Rarely do they fully report all of the prices of different dishes that they chose in the restaurant. The user is unlikely to be fully informed about how much she is going to spend. For these reasons, we assume that cost is also an attribute that the user has to learn. Uncertainty will still exist after she reads many reviews with divergent reported costs. After visiting the restaurant, however, the user may no longer have uncertainty about the cost.

Assume that for an attribute A (e.g., quality Q in Equation (1)) of the restaurant, reviewer k reports L evaluations, $\mathbf{R}_{kj} = \{R_{kj}^1, \ldots, R_{kj}^L\}$ (for example, rating and content).[12] These evaluations reflect the reviewer's consumption experience of the attribute, A_{kj}, which is assumed to be

$$A_{kj} = A_j + \xi_{kj}, \tag{3}$$

where A_j is the mean consumption experience across all consumers if they dine at the restaurant, and ξ_{kj} is a stochastic component with a variance $\sigma^2_{\xi,j}$ over the whole consumer population.

We further specify the relationship between the review evaluations and A_{kj} as

$$\mathbf{R}_{kj} = A_{kj} \cdot \mathbf{e}_L + \boldsymbol{\varepsilon}_{kj}, \tag{4}$$

where $\mathbf{e}_L$ is an $L \times 1$ vector with every element being 1, and $\boldsymbol{\varepsilon}_{kj}$ is another $L \times 1$ vector representing the deviations from the true experience. These deviations may come from, for example, the categorical quality rating (from 1 to 5) at Dianping, which does not exactly measure the reviewer's experience. Even a detailed description in content may not fully capture the total experience. These error terms are needed for our model to explain why evaluations for the same attribute are not perfectly aligned in the data. Rating and content can be perceived by users to have different accuracy in reflecting the true experience because of the difference between using a numerical scale and using contextual description.

In this paper, we propose and estimate two different learning models. We call the first model the *undifferentiated learning* model. We assume that the user learns about the overall distribution of restaurant attributes across the entire consumer population. The information value of every review is the same, i.e., each review has the same weight in the updating process. This model is similar to the established learning models in the marketing literature (e.g., Erdem and Keane 1996), except that we assume that the user will update her belief of $\sigma^2_{\xi,j}$, the variance of consumption experiences across all consumers. Therefore, the diversity of review evaluations, $\mathbf{R}_{kj}$, will increase the user's posterior $\sigma^2_{\xi,j}$ and, through Equation (1), will impact the restaurant choice. Because the learning model is similar to the previous literature, we describe the derivation of the updating process of this learning model in §§1 and 2 of the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mksc.2015.0926). We also include a numerical example to illustrate why the diversity of reviews can have a significantly negative impact on the choice of a risk-averse consumer.

We call the second model the *differentiated learning* model. It differs from the first model by assuming that a user learns about an individual specific consumption experience, A_{ij}, from reviewers' evaluations, based on her perceived taste correlations with the reviewers.

In our context, a review may be perceived as more informative than the others and will have a larger weight in the learning process. There may be two reasons for this heterogeneity: (1) The user may consider the reviewer's tastes for attributes more similar to her own; (2) The user may consider the reviewer's evaluations to have less noise reflecting the true consumption experiences.

To capture the first reason that some reviews will have a larger weight, which is the similarity between the user's and the reviewer's tastes, we introduce a correlation coefficient δ_{ik} that captures the heterogeneity. We assume that the prior beliefs of user i about her

[12] In our empirical context, $\mathbf{R}_{kj}$ for quality is two-dimensional (rating and content), whereas that for cost is a scalar. Learning is separate for quality and cost.

own consumption experience, A_{ij}, and reviewer k's experience, A_{kj}, are the following:

$$\begin{pmatrix} A_{ij} \\ A_{kj} \end{pmatrix} \sim N\left(A_0, \begin{pmatrix} 1 & \delta_{ik} \\ \delta_{ik} & 1 \end{pmatrix} \cdot \sigma_{e,j}^2\right), \qquad (5)$$

where A_0 is the user's prior belief of the restaurant's attribute, and δ_{ik} the perceived correlation between her taste and the reviewer's taste. Its value is restricted between 0 and 1.[13] We specify that $\sigma_{e,j}^2 = \tilde{\tau}_0^{-1} \cdot \sigma_{\xi,j}^2$, where $\tilde{\tau}_0$ is a scalar representing the ratio between the two variances. Given A_{ij}, we can express A_{kj} as the following:

$$A_{kj} \mid A_{ij} = (1-\delta_{ik})A_0 + \delta_{ik}A_{ij} + \sqrt{1-\delta_{ik}^2}\, e_{ikj}, \qquad (6)$$

where e_{ikj} is an error term distributed as $N(0, \tilde{\tau}_0^{-1} \cdot \sigma_{\xi,j}^2)$. We assume that, conditional on A_{ij}, e_{ikj} and $e_{ik'j}$ for any two reviewers k and k' are perceived by the user to be independent of each other.

To model the second reason that some reviews will have a larger weight, i.e., the noise reduction effect, we include a parameter λ_k in the error term. We assume that the random error $\boldsymbol{\varepsilon}_{kj}$ in Equation (4) follows a normal distribution,

$$\boldsymbol{\varepsilon}_{kj} \sim N(\mathbf{0}, \lambda_k^{-1}\Omega\sigma_{\xi,j}^2), \qquad (7)$$

where λ_k is a scalar. The $L \times L$ matrix Ω captures the correlations between different error components. The top-left element $\Omega[1,1]$ is normalized to 1, so $\lambda_k^{-1} \cdot \sigma_{\xi,j}^2$ represents the variance of the first evaluation, R_{kj}^1 (e.g., the rating); thus, λ_k measures the accuracy with larger λ_k implying that the evaluation is more accurate. The lth diagonal element in Ω, $\Omega[l,l]$, measures the ratio of the variance of the lth evaluation (e.g., the content) relative to the variance of the first evaluation. An off-diagonal element $\Omega[l,m]$ measures the correlation between the lth and the mth evaluations of the same attribute. The parameter λ_k captures the second reason for the heterogeneity in reviews.

Substituting Equation (6) into (4), we have

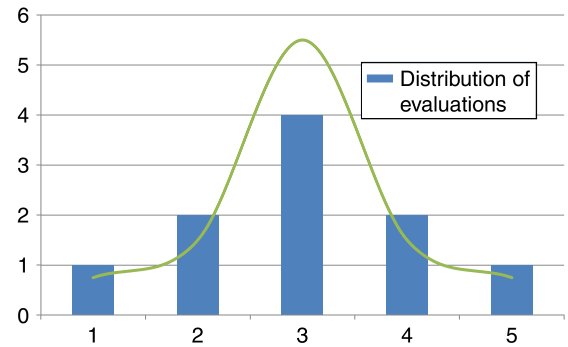
$$\mathbf{R}_{kj} = (\mathbf{1}-\boldsymbol{\delta}_{ik})A_0 + \boldsymbol{\delta}_{ik}A_{ij} + \mathbf{u}_{ikj}, \qquad (8)$$

where, $\boldsymbol{\delta}_{ik} \equiv \delta_{ik} \cdot \mathbf{e}_L$, and $\mathbf{u}_{ikj} \equiv \sqrt{1-\delta_{ik}^2}\, e_{ikj} \cdot \mathbf{e}_L + \boldsymbol{\varepsilon}_{kj}$. Assuming that e_{ikj} and $\boldsymbol{\varepsilon}_{kj}$ are uncorrelated, the variance-covariance matrix of $\mathbf{R}_{kj}$ for reviewer k and restaurant j is

$$\mathrm{Var}(\mathbf{R}_{kj}) = (((1-\delta_{ik}^2)\tilde{\tau}_0^{-1}) \cdot \mathbf{e}_L\mathbf{e}_L' + \lambda_k^{-1}\Omega)\sigma_{\xi,j}^2 \equiv \tilde{\Omega}_{ik}\sigma_{\xi,j}^2. \qquad (9)$$

[13] In a more general setting, δ_{ik} can be negative as the user may perceive the reviewer's taste opposite to hers. Because in this study we only focus on quality and cost, the restriction that A_{ij} and A_{kj} are positively correlated seems to be a reasonable assumption.

Figure 1 (Color online) Distribution of Reviews



After reading reviews, the user may learn the mean and variance of consumption experiences in the consumer population, as in undifferentiated learning. However, she can also use the correlation of tastes $\boldsymbol{\delta}_{ik}$ to learn *her own* A_{ij} projected from the reviews. Learning A_{ij} is more informative than learning the population mean A_j, and further reduces her uncertainty.

We assume the initial distribution of $\sigma_{\xi,j}^2$, before the user reads any reviews about the restaurant, to be inverse Gamma. Conditional on $\sigma_{\xi,j}^2$, the prior belief of A_{ij}, as implied in Equation (5), is $A_{ij} \mid \sigma_{\xi,j}^2 \sim N(A_0, \tilde{\tau}_0^{-1}\sigma_{\xi,j}^2)$. These are the beliefs before she reads any reviews. Using Bayes rule, the marginal distribution of A_{ij}, given the information set I_K, is a t-distribution with mean and variance as

$$E(A_{ij} \mid I_K) = A_{ijK}; \quad \mathrm{Var}(A_{ij} \mid I_K) = \frac{1}{\tilde{\tau}_{ijK}} \cdot \frac{b_{ijK}}{a_{ijK}-2}. \qquad (10)$$

The derivations and the specification of all updated parameters are in §3 of the online appendix. With the updated variance for A_{ij}, the expected utility function, after reading K reviews, Equation (1) can be rewritten as follows:

$$E[U_{ij} \mid I_K] = \alpha_{ij} + w_i^Q\{Q_{ijK} + \gamma_i^Q Q_{ijK}^2 + \gamma_i^Q \cdot \mathrm{Var}(Q_{ij} \mid I_K)\} + w_i^C C_{ijK} + \epsilon_{ij}, \qquad (11)$$

where Q_{ijK} and C_{ijK} are updated means, and $\mathrm{Var}(Q_{ij} \mid I_K)$ is the updated variance of Q_{ijK}.

A Numerical Example: Figure 1 shows the distribution of 10 evaluations of quality (one reports a rating 1, two report 2, four report 3, two report 4, and one reports 5) of a restaurant. The average is 3 and the variance is 1.2. The true population distribution of ratings is the curve in the figure with mean at 3 and variance at 0.9. Table 4 shows three scenarios with different correlations (δ_{ik}) with reviewers: In scenario A the three reviewers who gave ratings 4 and 5 have the highest correlation (0.8); in scenario B they have the lowest correlation (0.2). In scenario C ratings and correlations are independent.

Table 4 Reviewer Rating and Consumer Perception Correlation

		Scenario A	Scenario B	Scenario C
Reviews	Rating	Correlation weight	Correlation weight	Correlation weight
1	1	0.2	0.8	0.5
2	2	0.2	0.8	0.2
3	2	0.2	0.8	0.8
4	3	0.5	0.5	0.2
5	3	0.5	0.5	0.5
6	3	0.5	0.5	0.5
7	3	0.5	0.5	0.8
8	4	0.8	0.2	0.8
9	4	0.8	0.2	0.2
10	5	0.8	0.2	0.5

The updated expected qualities in the three scenarios are 3.64, 2.36, and 3.00, and the updated variances are 0.20, 0.20, and 0.22, respectively.[14] These results suggest that, when the user is more correlated with reviewers with high ratings (scenario A), the updated expected quality level is the highest, and vice versa if these reviewers report low ratings (scenario B). Furthermore, if reviewers who are perceived to have high correlations consistently report high (scenario A) or low (scenario B) ratings, the updated variance will become smaller (compared with scenario C). The interaction between reviewers' opinions and how reviewers' tastes are perceived to be correlated with the user's taste hence affects the learning process as well as the choice. This interaction effect is not captured in the simple reduced-form regressions in Table 3. This suggests the importance of structurally modeling consumer learning based on the heterogeneity of reviews, reviewers, and users.

As we will provide more details in §4, we assume and test from data how the additional information that supplements each review, such as the reviewer's star status and the number of helpful votes, will impact the heterogeneity in the taste correlation and enable users to learn own consumption experience. As this learning is more informative than the undifferentiated learning, information on reviewers and reviews can enhance the economic value for consumers. To our knowledge, traditional learning models in the marketing literature will not generate such an implication.

4. Estimation Results

In this section, we first discuss some details in model estimation and how we select the model specification that fits our data. Then we discuss the results from the chosen specification, which are used for the counterfactuals that measure the economic value of online reviews.

4.1. Model Specification, Identification, and Estimation

Model Specifications and Estimation. We model users' learning of restaurant quality based on reviewers' ratings ("rating") and detailed comments ("content") of restaurants. We rescale the rating to the range of $[-1, 1]$ by a linear transformation, to make the measurement consistent with the range of content so that the means and variances of both can be compared. Because there are few comments on price, we assume that the learning of cost relies solely on the reported average spending per person. Furthermore, to reduce the dimensionality of the parameter space, we restrict parameters α, w^Q, w^C, and γ^Q in Equation (1) to be homogeneous across individuals; thus, we focus on the consumer heterogeneity in the learning process.

To model differentiated learning, we construct multiple variables associated with each review and then classify them into two categories. The first category, W_{ik}, is used to model the taste correlation δ_{ik}. These variables include the star status of the user ("ustar") and the reviewer ("rstar"), which can indicate whether they belong to the same type of consumers in terms of how often they go to restaurants (assuming there is a direct correspondence between review contribution and restaurant visits). We also include the number of helpful votes ("votes") a review receives and the length of the review content ("length"), because reviews with more helpful votes from other users and more detailed comments may be more persuasive in affecting a user's preference. To further capture the rich heterogeneity in how the user may perceive the taste correlation (e.g., only star users share similar tastes with star reviewers[15]), we also include the interaction terms of these variables. We then model the correlation parameter as

$$\delta_{ik} = \frac{\exp(W_{ik}\alpha^{\delta})}{\exp(W_{ik}\alpha^{\delta})+1}. \tag{12}$$

The second category of variables, Z_k, pertains to the perceived accuracy of a review. We use two variables that relate to where the review is placed: "review page" measures the page on which the review is displayed, and "review position" measures the order in which the review is displayed in a page. The accuracy λ_k is modeled as

$$\lambda_k = \exp(Z_k\alpha^{\lambda}). \tag{13}$$

[14] We assume the following priors in the calculation: $\lambda_{ik} = 1$ for all reviews, $A_0 = 3$, $\tau_0 = 1.0$, $a_0 = 3$, and $b_0 = 0.45$.

[15] "Star users" and "star reviewers" refer to the website users/reviewers with higher star status levels (i.e., 2 or above). The terms are used to distinguish from users/reviewers with lower star status levels (i.e., 0 or 1).

Table 5 Description of Model Variables

Variable	Description	Mean	S.d.
W			
ustar	The star level of the user	1.5	1.5
rstar	The star level of the reviewer	1.8	1.5
ustar · *rstar*	User star interacts with reviewer star	2.6	4.2
votes	Number of helpful votes	1.2	0.9
votes · *ustar*	Number of helpful votes interacts with user star	1.8	2.8
votes · *rstar*	Number of helpful votes interacts with reviewer star	2.6	3.7
length	Length of content	0.8	0.7
length · *ustar*	Length of content interacts with user star	1.1	2.0
length · *rstar*	Length of content interacts with reviewer star	1.6	2.3
Z			
review page	(Log of) which page the review is displayed	0.4	0.6
review position	(Log of) the order of the review in a page	1.5	0.7

We choose these two variables because, by default, reviews are sorted by the time of posting. Reviews that appear at the bottom of a review page or in later pages may be perceived as more outdated; thus their rating and content are less accurate. They will be assigned a lower weight in the Bayesian updating process and will have less impact on the restaurant choice. Table 5 provides a description of the variables in W_{ik} and Z_k as well as their means and standard deviations.

For undifferentiated learning, reviewers' tastes are assumed to be independent from users' tastes, conditional on the mean, and we do not have the δ_{ik} correlation term. The perceived λ_k is also restricted to be the same across reviews for every user.

Using differentiated learning, a user must invest more cognitive resources since she has to process information from W_{ik} and Z_k. If the user believes the added value from differentiated learning is low, she will not expend the required resources; hence, only the population mean and variance will affect her restaurant choice. If she adopts differentiated learning, however, the population mean and variance are no longer useful as they are less informative than her own taste A_{ij} that has been learned. Therefore, for each restaurant attribute, we assume that undifferentiated or differentiated learning, but not both, affect the utility function. With two attributes (quality and cost), there are four possible combinations of learning mechanisms: (A) undifferentiated quality learning and undifferentiated cost learning; (B) undifferentiated quality learning and differentiated cost learning; (C) differentiated quality learning and undifferentiated cost learning; and (D) differentiated quality learning and cost learning.

Last, returned visitors have dined at reviewed restaurants within the previous 30 days. We allow for the possibility that the previous consumption experience may affect their prior uncertainty before reading online reviews. We assume that the prior uncertainty of returned visitors for the population mean A_j in undifferentiated learning is $(\alpha_{\text{return}}\tau_0)^{-1} \cdot \sigma^2_{\xi,j}$, and that for individual A_{ij} in differentiated learning is $(\alpha_{\text{return}}\tilde{\tau}_0)^{-1} \cdot \sigma^2_{\xi,j}$. If α_{return} is larger than one, returned visitors will have less prior uncertainty than new visitors before reading reviews; hence, their restaurant choice will be less influenced by reviews as implied in our learning model.[16]

We estimate the model by maximizing the likelihoods of users' choices. Conditional on the parameters in the learning models, we compute the updated beliefs of quality and cost after a user reads reviews of different restaurants in the choice set. Conditional on the beliefs and the parameters in the expected utility function, we then calculate the MNL probabilities that the user chooses one of the seven focal restaurants, one of the outside restaurants or the no-choice option. We search for model parameters in the parameter space until the log-likelihood function value is maximized.

Model Identification. The learning process is identified from the data on what reviews have been read and the data on which restaurant is chosen. Identification of the taste correlation δ_{ik} in differentiated learning comes from how different types of users when exposed to different reviews from different types of reviewers will make different choices. For example, suppose users are less likely to choose a restaurant when they are exposed to low evaluations from star reviewers, and vice versa when exposed to high evaluations from star reviewers, then this will indicate that users perceive a large taste correlation δ_{ik} for star reviewers. If, however, we observe that only star users and not nonstar users are influenced by the reviews from star reviewers, then, this will imply that δ_{ik} is only large for the pair of star user and star reviewer. A similar argument is applicable to how we identify the effects of other variables in W_{ik} on δ_{ik}.

How different variables in Z_k influence the likelihood of restaurant choice will identify the function for λ_k. For example, suppose users, after reading reviews on the top of review pages that report low ratings or content, are less likely to visit a restaurant than those who read similar reviews at the bottom of review pages. This implies that the position of reviews has a strong effect on their perceived accuracy. This example, however, also demonstrates that it is difficult

[16] We assume that own prior consumption experience does not impact the uncertainty of the variances.

to infer from restaurant choice whether a variable influences the accuracy λ_k or the taste correlation δ_{ik} because one can also assume that review position has increased the perceived taste correlation. We acknowledge that identification of λ from δ has relied on a priori assignment of the variables in W_{ik} and Z_k.[17]

With the identification of δ_{ik} and λ_k, the identification of other model parameters in undifferentiated and differentiated learning models is the same. Users who are exposed to more diverse opinions in reviews will have a larger updated variance[18] because there is one-on-one mapping from the variance of reviews to the variance. Different levels of variances in reviews, as shown in the reduced-form regressions in Table 3, will lead to different restaurant choices. These data observations help us to infer the risk preference parameters in the utility function.

For the variance-covariance matrix of the noise associated with rating and content, we first normalize $\Omega[1,1]$ to be 1. Hence, $\lambda_k^{-1}\sigma^2_{\xi,j}$ in Equation (7) represents the magnitude of the noise in rating. When λ_k is small, the uncertainty remains large even after the user reads many reviews, so her restaurant choice is barely affected. If $\Omega[2,2]$ is larger than one, restaurant choice will be less affected by content than rating, and vice versa. For $\Omega[1,2]$, the covariance of the noise in rating and content, the intuition of the identification is as follows: Consider the scenario wherein two sets of reviews have the same average rating and content. Suppose content and rating are positively correlated in the first and negatively correlated in the second. If, after reading the reviews, consumers' restaurant choices are more affected by reviews with positive correlation than reviews with negative correlation, we can infer that $\Omega[1,2]$ is positive. This is because rating and content in the first set of reviews are consistent with the perceived correlation, so consumers will have less uncertainty after reading the reviews. Overall, the identification of Ω mainly relies on how the variations in rating and content affect restaurant visits.

Without detailed data on reviews, estimating the learning of quality and cost is challenging. Previous literature on learning has used data outcomes to identify multiple-attribute learning (e.g., Crawford and Shum 2005 and Chan et al. 2013). We do not observe actual consumption experiences after restaurant visits in data;[19] therefore, our identification is based on the input variation, i.e., reviews on quality and price, and their impact on consumers' restaurant choice.

To demonstrate that our learning model is identifiable and that the estimation procedure is valid, we conduct a simulation study. We assign "true" values for all model parameters and simulate consumer restaurant choices based on the reviews that users read in our data. We then estimate the choice model from the simulated data. Results show that the true values for all parameters can be statistically recovered.[20]

Model Selection. We estimate and compare Models (A) to (D) to test the consumer learning mechanism for quality and cost. Model comparison statistics are reported in Table 6. Model (A), undifferentiated learning for quality and cost, is the most parsimonious with 17 parameters. Model (D), differentiated learning for quality and cost, has the largest number (41) of parameters and also the highest log-likelihood value. Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), Model (C), differentiated learning for quality and undifferentiated learning for cost, is the best specification that fits with data. To test the robustness of this model selection, we also estimate a latent-class model by allowing four segments of users, who learn about quality and cost using different combinations of learning strategies as in Models (A) through (D). We find that the segment size of users who use differentiated learning for quality and undifferentiated learning for cost (88.0% with a t-value of 2.02) dominates the sizes of other segments. Again, this supports the selection of Model (C).

A potential explanation as to why differentiated learning is adopted for quality is that it is a subjective measure that is perceived by individuals differently.

[17] We need better data to identify the accuracy of reviews from the correlation of tastes. For example, if some consumers tastes are negatively correlated, reading a positive review may reduce the expected quality but also simultaneously reduce the level of uncertainty. These opposite forces may help separate λ from $\boldsymbol{\delta}$. Alternatively, one may model the consumer search process to better identify the learning mechanism. Suppose reviews from star reviewers are perceived as more accurate. The search process will be shorter if a user has read reviews from star reviewers. Yet if star reviewers only affect the user's perception of taste correlation, their reviews will impact the user's restaurant choice but not necessarily the search process.

[18] Parameters for priors, including A_0, a_0, b_0, and τ_0, are calculated from the data. We calculate the mean ratings and mean costs of the restaurants and use them as restaurant specific A_0 for quality and cost, respectively. This implies that users have rational prior beliefs; thus, the economic value of reviews for consumers is driven by reducing their uncertainties, not by correcting biased beliefs. For the variance of quality, we set $a_0 = 3$ and $b_0 = 0.12$, and for the variance of cost, $a_0 = 3$ and $b_0 = 0.16$, such that the prior beliefs of the variances are consistent with the distributions of quality ratings and reported costs in all reviews in the data. Finally, we set $\tilde{\tau}_0 = 1$, such that the uncertainty of the prior belief of A_{ij} is the same as $\sigma^2_{\xi,j}$.

[19] We find that only six users visited a restaurant, then returned and provided reviews for those restaurants. It is hard to make any meaningful inference based on the small number of observations.

[20] Results from the simulation study are available from the authors on request.

Table 6 Model Fit Comparisons

	Quality learning	
	Undifferentiated learning	Differentiated learning
Cost learning		
Undifferentiated learning		
Log-likelihood	−5,197.7	−5,117.3
Number of parameters	17	29
AIC	10,429.5	10,292.5
BIC	10,550.1	10,498.3
Differentiated learning		
Log-likelihood	5,178.0	−5,108.0
Number of parameters	29	41
AIC	10,414.1	10,298.1
BIC	10,619.9	10,589.0

Note. Number of observations = 8,918.

Thus, learning the average opinions among reviews is not very useful for decision making. Differentiated learning provides more informational value to a user through learning her own preference. The value may dominate the price of the cognitive resource she must use. Cost, on the other hand, is more objective; hence, each reported cost is equally reliable. Consequently, the useful information for cost is the overall distribution of how much people spend in the restaurant, which is the target of undifferentiated learning.

4.2. Parameter Estimates

Estimation results of Model (C), with differentiated learning for quality and undifferentiated learning for cost, are reported in Table 7. The significant estimates for the utility weight and risk for quality indicate that consumers prefer high quality and low risk. The utility weight for cost (in 100 CNY) is negative and significant as well, consistent with the reduced-form regression results. The large magnitude of the estimated quality weight suggests that quality is more important than cost in consumers' choices.

For the perceived taste correlation in differentiated learning, the negative estimate for "ustar" (−1.07) shows that users with high star status believe that their tastes are less correlated with reviewers. The negative estimate for "rstar" (−1.38) also suggests that an average user believes that the taste of nonstar reviewers is more correlated with theirs. The positive interaction term between "ustar" and "rstar" (0.36), however, implies that a star user associates herself more with star reviewers. These results suggest that users perceive how their tastes match with reviewers' tastes based on the similarity in star status. Online review websites may match users with reviews written by users with similar star status because users can learn more from these reviews.

For other parameters, the effect of helpful votes ("votes") is not significant, but the negative estimate for the interaction effect "votes · rstar" (−0.97) suggests that helpful votes can increase the perceived preference correlation with nonstar reviewers (relative to star reviewers) for a user. Star users are more likely to use the information (i.e., the estimate of "votes · ustar" is 0.57) perhaps because they are more knowledgeable. Furthermore, the estimate of "length" (−2.02) shows that users are less likely to associate their tastes with reviews with lengthy comments. We find from Dianping that long comments usually discuss topics irrelevant to the quality of restaurants. Users might be distracted by such loaded information and skim through lengthy comments.

As to the reviews, the negative estimates for "review page" (−4.00) and "review position" (−0.28) imply that old reviews are perceived as less informative. In the correlation matrix Ω, the significantly positive estimate for the correlation coefficient Ω[1, 2] (0.65) indicates that rating and content are perceived to be consistent. The ratio of content variance to rating variance, Ω[2, 2] (0.70), is significantly smaller than 1, indicating that users perceive content to have less noise than rating. In the learning process, therefore,

Table 7 Estimates of the Proposed Learning Model

Parameters	Estimate	*t*-value
Utility parameters		
Store dummies	Not reported	Not reported
Quality weight (W^Q)	**4.32**	4.43
Risk parameter for quality (γ^Q)	**−3.45**	−9.53
Cost weight (W^C)	**−1.44**	−2.10
Intercept for outside restaurants	**−3.94**	−34.76
Ratings for outside restaurants	**0.50**	10.99
Taste correlation δ		
intercept	**4.35**	2.12
ustar	**−1.07**	−2.05
rstar	**−1.38**	−1.97
ustar · rstar	***0.36***	1.73
votes	−1.21	−1.23
votes · ustar	***0.57***	1.93
votes · rstar	**−0.97**	−2.43
length	***−2.02***	−1.91
length · ustar	0.13	0.46
length · rstar	0.51	1.11
Accuracy for quality λ^Q		
intercept	−0.20	−0.50
review page	**−4.00**	−2.04
review position	**−0.28**	−1.96
Correlation matrix Ω		
Correlation coefficient (Ω[1, 2]) *between rating and content*	**0.65**	9.28
Ratio of content variance to rating variance (Ω[2, 2])	**0.70**	12.04
Inverse of the prior uncertainty for repeat visitors		
quality	**0.43**	2.56
cost	7.77	0.30
Log likelihood	−5,117.3	

Note. Significant codes: Bold: 0.05 significant; bold and italic: 0.1 significant.

content has a stronger impact than rating on consumers' learning. This result suggests that, to enhance the informational value of reviews, it is important to incentivize reviewers to provide contextual descriptions for their consumption experiences.

Finally, we test whether returned visitors already learned the quality and cost of restaurants from their own consumption experience and thus have less uncertainty. The estimate of the inverse of the prior uncertainty for quality (0.43), however, is significantly smaller than one, suggesting that the previous consumption experience does not resolve the uncertainty. We believe that the reason for this surprising result is that consumers self-select to search for information. Those who check for reviews after visiting the restaurant are likely to be more uncertain about the restaurant quality probably because they found their consumption experience inconsistent with their expectations. For this group of consumers, the information from online reviews is still important after restaurant visits. The estimate for the prior uncertainty of price (7.77), though insignificant, is much larger than one, suggesting that users will have a good knowledge of the cost after one restaurant visit. Reviews will no longer provide useful information.

5. The Economic Value of Online Reviews

We use a series of "what-if" scenarios to study the economic value of online reviews at Dianping. We first assume that there is no Dianping.com, and that users can only make decisions based on their priors for quality and cost. Next, to understand which restaurant attribute reviews bring the most value to users, we assume that Dianping provides no information on quality or cost, so that users can only make decisions based on prior belief about quality or cost. We further study the economic value of different information components associated with reviews. We take away, one at a time, the information of rating, content, star status, and helpful votes. When star status or helpful votes is removed, we assume that consumers treat all reviews as having equal star status and the same number of votes (we use the averages in data). Because these information components do not independently impact consumer learning, the results represent the marginal effect of each piece of information on the consumer value, when other components remain unchanged. The last scenario studies the effect of a possible restriction on the length of reviewer comments. We reduce the maximum length of content from 1,000 to 300 characters and truncate all lengthy reviews to this new maximum.

To measure the economic value, we make several key assumptions: First, we assume that reviewers represent the consumer population in terms of the consumption experiences, and that their rating and content are unbiased (as already assumed in our model). Second, we assume that users can correctly infer the taste correlation δ's, in differentiated learning for quality, based on the information about reviews and reviewers provided on Dianping. Consequently, for the majority of consumers, the more information provided in each review the less likely they are to make wrong decisions. Without these two assumptions, we cannot tell whether consumers are making the right decisions; thus, the value of reviews cannot be measured. Finally, we also assume that consumers do not have other information sources to substitute for Dianping. When Dianping.com is removed in one of the "what-if" exercises, for example, users are assumed to make choices based on their priors instead of switching to learn from other sources. Without this assumption we cannot predict what choices will be made; thus, again, the value of reviews cannot be measured. Our results probably better reflect the value for less resourceful consumers because of this assumption.

5.1. The Value of Information for Consumers

The value of information for consumers comes from the fact that consumers are more likely to make the right choice given more information. We simulate consumer choices in each "what-if" scenario. Suppose user i reads K reviews for a set of S_i restaurants. With the information set I_K, we first compute the updated beliefs for quality under differentiated learning and for cost under undifferentiated learning. We then simulate the stochastic term ϵ_{ij} to obtain the expected utility $E[U_{ij} \mid I_K]$. We also simulate the expected utility $E[U_{io}]$ for outside restaurants and $E[U_{in}]$ for the no-choice option.

The consumer chooses one of the restaurant options (inside, outside, and no-choice option) based on whichever option generates the highest expected utility. We then remove an information component X in each of the "what-if" scenarios. Denote the limited information set as $I_K \backslash X$.[21] We then calculate the new expected utilities $E[U_{ij} \mid I_K \backslash X]$ using the same procedure, with the same set of simulated stochastic terms ϵ_{ij} and calculate the new optimal choice $l(I_k \backslash X)$. If the consumer makes the exact same choice under these two conditions, then the value of information component X is zero; otherwise, the consumers would obtain different consumption utilities under these two choices. For example, if the consumer chooses restaurant option j under information set I_K, but restaurant j' under information $I_K \backslash X$, we can simulate the real consumption utility under these

[21] In the extreme scenario where Dianping is entirely removed, $X = I_K$.

Table 8 Economic Value of Information for Consumers

	Economic value (CNY)		
Information component	New visitor	Repeat visitor	Overall
Dianping total	6.11	10.41	6.68
Quality information	6.06	10.40	6.64
Cost information	0.04	0.02	0.04
Rating	0.51	0.77	0.56
Content	1.58	2.06	1.64
Star status	0.60	1.10	0.67
Helpful votes	0.11	0.23	0.14
Length of content	0.02	0.03	0.02

Note. Because there are interaction effects between the information components in the value function, the total information value is not equal to the sum of each component.

two choice scenarios and compute the difference of $\Delta U_i(X) = U_{ij} - U_{ij'}$. To compute the consumption utility, we simulate the ex-post quality experience, if the user eats at the restaurant, from her updated posterior distribution under information I_K.[22] We also simulate the actual cost of dining based on the posterior distribution. We repeat the procedure 100 times, and calculate the average of the differences across simulations to obtain the expected utility change, $\Delta EU_i(X)$. The difference $\Delta U_i(X)$ under each draw can be positive or negative. However, since we assume that the information is unbiased, the average of the differences across all simulations, $\Delta EU_i(X)$, will be positive.

We then calculate the gain or loss in terms of monetary value by making the utility change equal the utility change when she pays an amount $V_i(X)$. From the utility function in Equation (1), this can be calculated as: $V_i(X) = -\Delta EU_i(X)/w_i^C$. Finally, we calculate the average of $V_i(X)$ across all users observed in data as the measure of the consumer value for the information component X.

The change in consumer value per user generated from different information components are presented in Table 8. We also separately report the value for new visitors and returned visitors. Because returned visitors (in our sample) have less precise priors about the quality, the effects of different information components are in general higher for returned visitors. The consumer value generated from reviews at Dianping, reported in the first row, is 6.1 CNY for each new visitor and 10.4 CNY for each returned visitor. Overall the average value is 6.7 CNY per user. Assuming that a user brings two friends to the restaurant, and that the average cost per person is 85 CNY as in the data, the value is about 3% of the total expense. As Dianping attracts over 30 million unique visitors every month, the aggregate economic value that Dianping brought to consumers is estimated to be 210 million CNY a month, assuming that the users in our sample represent the population of visitors at Dianping.

The next two rows in the table break down consumer value based on quality and cost information. Quality information has the dominant share of the total value. This is because the estimated cost weight is small (relative to quality parameters, as shown in Table 7), and the differences in dining cost are not too large between restaurants (see Table 1). The value of cost information may be higher in other settings. Furthermore, in undifferentiated learning, users only use the information to update their beliefs on the average and variance of costs across reviewers. This is less valuable compared to using differentiated learning to learn own taste for restaurant quality. The provision of cost information therefore rarely changes consumers' choices.

The next five rows in the table report the marginal effects of different information components on consumer value. Both rating and content provide information on restaurant quality, but the effect of the latter dominates the former because users perceive that content is more accurate. The marginal effect of content on consumer value is about 24% of the total value from the quality information. This suggests that content cannot be substituted by other information components of reviews.

For the information components that affect the taste correlation δ_{ik} in differentiated learning, only the star status of reviewers has a significant marginal effect, i.e., about 10% of the total economic value. This information helps users to learn their tastes from reviewers of the same type. Although the marginal effect of "helpful votes" is negligible, the real reason that Dianping offers this feature is perhaps to motivate reviewers to provide more feedback and thus receive more votes. This provides an indirect contribution to the value of reviews, which has not been measured. Finally, limiting comments from 1,000 to 300 characters at most does not change the consumer value. This suggests that Dianping may restrict reviewers to writing shorter (but useful) comments, so that users can read more reviews in a single Web page.

5.2. The Value of Information for Restaurants

The economic value of online reviews for restaurants comes from how they affect the probability of consumer visits. Whereas reducing uncertainty will increase users' expected utility, reviews might also reduce the expected quality, depending on what reviews users read. The expected probability for user i to visit restaurant j is θ_{ij} as in Equation (2). Thus, the change in the visiting probability when review feature X is removed is

$$\Delta\theta_{ij}(X) = \theta_{ij}(I_K) - \theta_{ij}(I_K \backslash X).$$

[22] In this way we implicitly assume that the updated belief is unbiased. The more reviews the user reads, the smaller the updated variance; thus, the belief is closer to the true consumption experience.

Table 9 Economic Value of Information for Restaurants

Information component	Economic value (CNY) More popular restaurants	Less popular restaurants	Overall
Dianping total	9.56	8.37	8.63
Quality information	9.34	8.38	8.59
Cost information	0.71	−0.17	0.03
Rating	−2.67	−2.38	−2.45
Content	1.18	3.09	2.67
Star status	2.03	2.55	2.44
Helpful votes	0.87	0.66	0.71
Length of content	−0.18	−0.34	−0.30

Note. Because there are interaction effects between the information components in the value function, the total information value is not equal to the sum of each component.

Assume that the user brings two friends and that each person pays 85 CNY. Also assume that the average profit margin for restaurants is 30%, so the profit of a visit is about 77 CNY for the restaurant. The economic value of information X to restaurant j is $V_{ij}(X) = 77 \times \Delta\theta_{ij}(X)$. Summing up across the seven restaurants, and taking the average across all observations, we can obtain the value for the seven restaurants for each browsing session.

Table 9 reports the results. The overall profit impact for the seven restaurants is about 8.6 CNY per browsing session. Given the 8,918 browsing sessions in the three-month sample period, this suggest that Dianping brings a 25,000 CNY profit increase for the seven restaurants in our sample, or about 3,600 CNY per month for each restaurant. In 2007 the average annual revenue of a restaurant in China was about 300,000 CNY (Chen 2008). The 3,600 CNY increase represents a significant contribution to the baseline profit, highlighting the importance of review websites for the business. We also classify the three restaurants in chain A as more popular since they have a higher conversion rate. We classify the rest as less popular. The value is much higher for popular restaurants, indicating that with lower uncertainty about quality and cost, users are more likely to choose popular restaurants. Similar to the results for the consumer value, the majority of the restaurant profit increase comes from information on the quality of restaurants. With ratings available, the marginal effect of content is 2.7 CNY, about 31% of the total value for restaurants. With content available, however, the marginal effect of ratings will reduce the restaurant profit by 2.5 CNY because the large diversity in ratings even for the same restaurant will increase users' updated variance of restaurant quality. Finally, the impact of other information components is negligible.

6. Conclusion

This paper proposes a new learning mechanism to study how reviews impact the consumer choice of restaurants. Calibrating our models on a unique data set provided by Dianping.com, we find that, for the learning of quality, consumers use the information provided from the website to distinguish the informational value of different reviews and learn own preferences. For the learning of cost, consumers focus only on the overall distribution summarized by the mean and the variance across consumer population. Based on estimation results, we conduct counterfactual experiments to study how consumers' choices would change under different information provision scenarios, and use the outcomes to measure the value of online reviews. We find that online reviews from Dianping generate value for consumers as well as restaurants because they reduce the uncertainty associated with consumption decisions.

There are several possible directions for future research. It will be interesting to further explore the underlying behavioral process for the effects of user and reviewer characteristics on consumer learning. Controlled experiments are desirable for this purpose. We acknowledge that the major limitations in this study are that we treat the choice set and the reviews that a consumer reads as exogenous. If consumers also use information from Dianping to form the choice set prior to reading reviews, the total economic value we calculated for consumers and restaurants may be biased downward. Furthermore, users can read more reviews if their uncertainties are not resolved; the optional value of reading more reviews has not been captured in the calculation of the economic value. To endogenize these decisions in the study, however, requires additional data on what information the consumer is exposed to prior to reading reviews. A structural information search model, together with the current consumer learning model, will vastly increase model complexity. Finally, this study ignores potential information spillovers from multiple browsing sessions of the same users. We hope this topic will be explored in future research.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0926.

Acknowledgments

The first three authors are listed in reverse alphabetical order. This paper is part of the first author's dissertation at Washington University in St. Louis. The authors thank the editor, associate editor, and two anonymous referees for extremely helpful comments. The authors also thank participants at the China India Consumer Insights Conference for their valuable comments. The second and fourth authors acknowledge the financial support from the National Natural Science Foundation of China [Grants 71428004 and 71422006].

References

Bye A (2009) Interview series: Tao Zhang from Dianping.com. Accessed April 15, 2012, http://www.web2asia.com/2009/07/08/interview-series-tao-zhang-from-dianping-com/.

Chan T, Narasimhan C, Xie Y (2013) Treatment effectiveness and side effects: A model of physician learning. *Management Sci.* 59(6):1309–1325.

Chan TY, Hamilton BH (2006) Learning, private information, and the economic evaluation of randomized experiments. *J. Political Econom.* 114(6):997–1040.

Che H, Erdem T, Oncu S (2015) Consumer learning and evolution of consumer preference. *Quant. Marketing Econom.* Forthcoming.

Chen F (2008) Dianping.com: The economics of word-of-mouth. *New Fortune* (October 23). http://www.xcf.cn/newfortune/cy/200810/t20081023_241743.htm.

Chevalier JA, Mayzlin D (2006) The effect of word of mouth on sales: Online book reviews. *J. Marketing Res.* 43(3):345–354.

Ching A, Erdem T, Keane M (2013) Learning models: An assessment of progress, challenges and new developments. *Marketing Sci.* 32(6):913–938.

Crawford G, Shum M (2005) Uncertainty and learning in pharmaceutical demand. *Econometrica* 73:1137–1174.

Erdem T (1998) An empirical analysis of umbrella branding. *J. Marketing Res.* 35(3):339–351.

Erdem T, Keane MP (1996) Decision-making under uncertainty: Capturing choice dynamics in turbulent consumer goods markets. *Marketing Sci.* 15(1):1–21.

Erdem T, Keane MP, Sun B (2008) A dynamic model of brand choice when price and advertising signal product quality. *Marketing Sci.* 27(6):1111–1125.

Harrison P, Stevens C (1976) Bayesian forecasting (with discussion). *J. Roy. Statist. Soc. B* 38(3):205–247.

Kalman RE (1960) A new approach to linear filtering and prediction problems. *Trans. ASME-J. Basic Engrg.* 82(1):35–45.

Moe WW, Trusov M (2011) Measuring the value of social dynamics in online product forums. *J. Marketing Res.* 48(3):444–456.

Roberts JH, Urban G (1988) Modeling multiattribute utility, risk and belief dynamics for new consumer durable brand choice. *Management Sci.* 34(2):167–185.

Szymanowski M, Gijsbrechts E (2012) Consumption-based cross-brand learning: Are private labels really private? *J. Marketing Res.* 49(2):231–246.

Zhao Y, Yang S, Narayan V, Zhao Y (2012) Modeling consumer learning from online product reviews. *Marketing Sci.* 32(1): 153–169.