Value of Multi-dimensional Rating Systems: An Information Transfer View

Completed Research Paper

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Abstract

This paper empirically examines the value of multi-dimensional online rating system (versus single-dimensional online rating system) from an information transfer perspective. Our key identification strategy hinges on a natural experiment that took place on TripAdvisor.com that allows us to identify the causal effect with a difference-in-difference approach. Our key findings, first show that consumers' ratings for the same restaurants are significantly higher in TripAdvisor after its adoption of the multidimensional rating system. Second, we show that restaurants with lower price level benefit more from rating system change. Third, we show that the ratings in single-dimensional rating system are similar to the lowest dimension in the multi-dimensional system. The results demonstrate the information value of multi-dimensional ratings. Our study provides important implications for a better design of online WOM systems to help consumers match their preferences with product/service attributes.

Keywords: multi-dimensional rating system, WOM performance, natural experiment, difference-in-difference

Introduction

The substantial increase of online word of mouth (WOM) in the form of online product reviews and ratings in retail websites has transformed the way consumers acquire product information. Online product reviews enable consumers to acquire product information and, at the same time, share product experiences. According to a recent report by The New York Times (2012), "reviews by ordinary people have become an essential mechanism for selling almost anything online".

One interesting aspect of online WOM systems is its design that guides consumers to obtain and share product experiences. Most online WOM platforms allow consumers to submit a numerical rating of the product, plus text reviews. Those numerical ratings are then aggregated and presented as an average value or a rating distribution. Notably, a majority of the current online product rating systems follow a single-dimensional system (e.g., Amazon.com, *Yelp*.com, etc.), with just a few exceptions (*TripAdvisor*.com, *OpenTable*.com). In a single-dimensional rating system, consumers report a single number, usually on a discrete interval scale of 1-5, as their overall level of satisfaction for the product/service, and they can also provide more details regarding their ratings with text reviews. Prior studies have focused on single numerical ratings in online product reviews in examining the impact of product ratings on sales, and mixed findings have been reported (Chevalier and Mayzlin 2006, Duan et al. 2008). One plausible explanation is that usefulness of single-dimensional rating system is questionable (at least for some products, such as books) because single-dimensional ratings ignore consumer heterogeneity in their multi-dimensional preferences (Godes and Silva 2012, Moe and Schweidel 2012). For example, when consumers plan to dine at a restaurant, they have different criteria for their preferences, such as food quality, food taste, restaurant ambiance, etc. Consumers rely on online ratings to seek information on either quality, to resolve product quality uncertainty; or match of preference, to resolve product fit uncertainty (Kwark et al. 2014). It is difficult for consumers' idiosyncratic preferences to be matched onto a single numerical rating in the single-dimension rating system. Multi-dimensional system has been proposed to address this challenge as it allows consumers to provide different ratings on different dimensions of the product/service that would reflect both quality and preference. As a result, it is likely that multi-dimensional rating system could help the matching process. The rationale behind this claim is that multi-dimensional rating system facilitates information transfer among consumers, so that it is easier for consumers to better choose a product that they are more likely to enjoy.

Due to the theoretical importance and practical significance of online WOM systems, information system (IS) scholars (Li and Hitt 2010, Archak and Ghose 2011) have called for rigorous examinations of the informational value of multi-dimensional rating systems. At first blush, a multi-dimensional rating system should increase information transfer efficiency because it allows consumers to share their consumption experiences in different dimensions and provides more information for consumers, especially when consumers value a product/service in different dimensions. And when such information transfer is efficient, consumers exposed to multi-dimensional rating systems prior to consumption are likely to make more effective decisions and are therefore more satisfied with their purchases. On the other hand, there are also reasons to believe that more information doesn't necessarily facilitate information transfer. First, excessive information could lead to cognitive overload. As the information contained in multi-dimensional rating system will lead to higher evaluation costs for consumers, it is not clear whether providing additional multi-dimensional ratings will provide a net increase in decision performance over a single rating (Simon 1982). In addition, in terms of implementation, re-designing a single-dimensional rating system into a multi-dimensional system is costly, and it can also be difficult and time-consuming for a reviewer to rate different dimensions, which could potentially lead to low quality rating in different dimensions and reduce information transfer efficiency. If all that matters is the aggregate single rating, then it may not justify adopting the multi-dimensional rating system. In sum, there is considerable value to examine whether multi-dimensional systems do make information transfer easier among consumers and quantify the economic value of redesigning a single-dimensional rating system into a multi-dimensional rating system.

The goal of this research is to directly examine and compare the efficiency in information transfer in the single and multi- dimensional rating systems. Particularly, we ask the following research question:

Do multi-dimensional rating systems enable more efficient information transfer among consumers?

The efficiency of information transfer can be examined by observing the dynamics of ratings over time and across different rating systems. When information transfer is efficient, consumers form more reasonable expectations of utility from consuming a product of interest and are therefore less likely to be "surprised" because the consumption utility is more likely to confirm the expected utility. As a consequence, we should observe less dissatisfied consumers and less variation in ratings *over time* when information transfer is efficient. Note that information transfer efficiency cannot be identified by estimating the impact of multi-dimensional ratings on sales. Consumers' post-purchase satisfaction is the right metric to understand information transfer efficiency. For example, a higher sales with most consumers being "dissatisfied" after purchases is actually a signal of low information transfer efficiency, because information does not help match consumers' preferences to their ideal products.

Besides comparing the relative performance of single versus multi-dimensional rating systems, we are also interested in several other empirical questions. Given products/services usually have different dimensions (e.g. location, service and food quality in a restaurant setting), it is interesting to understand how *consumers map multiple attributes into overall rating in a single-dimensional rating system vs. in a multi-dimensional rating system*. Answering this question sheds light on how different product attributes weigh in consumer utility and "are reflected" by ratings. Moreover, we also examine the role of *price* in single and multi-dimensional rating systems. Price has long been used as a signal of quality, when quality cannot be ascertained before purchase, from the economics and marketing literature. Given multi-dimensional ratings may facilitate communication of quality information, it will be interesting to examine the effects of price sensitivities of consumers when switching from a single-dimensional to a multi-dimensional rating system. If consumers find product quality could be ascertained, then they will rely less on price as a signal of quality. And if this is the case, then we should see different effects on high priced and low priced products. Particularly, lower priced products would benefit more from other quality signals.

To address our research questions, we collect observational data from three leading restaurant review websites (*Yelp*, *TripAdvisor* and *OpenTable*). *Yelp* maintains a single-dimensional rating system; *OpenTable* has a multi-dimensional rating system since its inception; *TripAdvisor* changed its rating system from single-dimensional to multi-dimensional during our sampling period. We sample 1207 restaurants in New York City, and obtain reviews for these restaurants on the three websites to construct our panel data. We then study how those same restaurants are being rated in these different rating systems. Our main econometric identification strategy hinges on the natural experiment that took place on *TripAdvisor* that changed its rating system from single-dimensional to multi-dimensional in January, 2009. And in the meantime, a similar review website, *Yelp*, did not make such a change. This system change allows us to specify our empirical model in a quasi-experimental Difference-in-Difference (DID) framework.

Several interesting results emerge from our econometric analyses. First, we estimate that after adopting a multi-dimensional rating system, on average, the overall ratings on *TripAdvisor* has increased by at least 0.176. This is consistent with the view that the multi-dimensional rating system enables and enhances information transfer among consumers more efficiently, leading to more effective purchase decisions and more satisfied customers. Second, consistent with the finding that the multi-dimensional system enhances information transfer efficiency, we show that ratings on multi-dimension rating systems are convergent. Third, we find that consumers weigh in different attributes when rating in a multi-dimensional system; while in a single-dimensional system, consumers' ratings reflect the experience in the least satisfied dimension in the multi-dimensional rating system. This finding provides a plausible explanation why information transfer efficiency is lower in a single-dimensional system. Moreover, we show that not all restaurants benefit the same from rating system change, in which, restaurants with lower price level would benefit more. This is again consistent with the view that multi-dimensional ratings help convey quality information more efficiently, and therefore consumers don't have to rely on price level to infer restaurant quality. Overall, our study makes a pioneering effort in establishing a causal effect of adopting a multi-dimensional rating system using a real-world quasi-natural experiment.

This paper proceeds as follows: Section 2 presents a survey of related literature. Section 3 describes the theoretical foundations and the proposed hypotheses. Section 4 and 5 presents the data, empirical methodologies and results of econometric analyses. In Section 6 and 7, we discuss the results, managerial and theoretical implications and future research with a conclusion of section 8.

Related Literature

There is a mature body of scholarly research on online product reviews as a form of WOM across different fields, such as information systems, marketing, economics and computer science. Much of the prior work has focused on the impact of WOM on sales as well as other performance metrics, such as firm values and adoption (e.g., Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Dellarocas et al. 2007, Duan et al. 2008, Forman et al. 2008, Moe 2009).

However, rating system design remains an important yet under-studied topic. As Archak, Ghose and Ipeirotis observe, "by compressing a complex review to a single number, we implicitly assume that the product quality is one-dimensional" (Archak et al. 2011), the single-dimensional view of online product reviews may not be informative when consumer tastes vary (Rosen 1974) and attributes offer idiosyncratic utility (as opposed to common utility) to consumers (Nelson 1981). Since aggregating or averaging consumer preferences is usually not meaningful (Theil 1971, Hong et al. 2012), this may partly explain the mixed findings of relationship between review valence and sales (Duan et al. 2008). Indeed, "review" literally means evaluation of a publication, product or service, which is not intended to only indicate the objective quality of a product, but more broadly about "opinion of the product" which may have a subjective element that is individual consumer-specific. Single-dimension rating system ignores consumers' heterogeneity and fit between product and consumers, resulting in a biased rating system. Li and Hitt (2008) find self-selection problem using Amazon book reviews data by showing that online reviews tend to trend downward overtime and may be a biased estimator. Their explanation is those who have the strongest preferences for the book may post higher ratings in the early stage. Godes and Silva (2012) investigate the impact of the sequence of ratings beyond the temporal effect. They find the ratings decrease sequentially. They argue that the increasing difficulty in diagnosticity assessment and decreasing similarity among consumers over the sequence could be the complimentary explanation. Consumers that experience extreme satisfaction or dissatisfaction might bring self-selection problem in reporting. Considering single-dimension rating systems are biased, information system (IS) scholars (Li and Hitt 2010, Archak and Ghose 2011) have called for rigorous examinations of the informational value of multi-dimensional rating systems.

Some pioneering research has attempted to explore different dimensions of product attributes with either econometric or text mining approaches such as natural language processing (NLP). Decker and Trusov (2010) estimate the relative effect of product attributes and brand names on the overall evaluation of the products. Ghose et al. (2012) estimate consumer demand and various product attributes based on hotel reservation data and consumer-generated reviews, and then they propose a ranking system according to estimated "expected utility gain" besides price and ratings. Ghose and Ipeirotis (2011) and Archak, Ghose, and Ipeirotis (2011) examine the impact of different product attributes and consumer opinions on review helpfulness and product sales. Ghose et al. (2009) demonstrate that different dimensions indeed affect sellers' pricing power differentially and that buyers look for a specific reputation dimension when they purchase from a specific seller. All of these research point out that consumers do take into consideration of and review different dimensions of a product before consumption, even within a single-dimensional rating system. However, there is no research directly examine the impact of multi-dimensional rating systems on matching consumer preferences with product attributes. Our research provides empirical evidence supporting this view that the multi-dimensional rating system significantly enhances information transfer efficiency and leads to more satisfied customers and more consensus of quality information.

Hypothesis Development

Expectation-Confirmation Theory

Expectation-confirmation theory (ECT) is widely used in the information systems and marketing literature to understand system adoption (Bhattacherjee 2001, Brown et.al 2012) and consumer satisfaction (Anderson and Sullivan 1993, Churchill and Suprenant 1982, Kim et al 2009, Oliver 1980). Drawing on adaptation level theory (Helson 1964), Oliver (1980) posited one's level of expectation about product performance to be an adaptation level. Post-decision deviations from the adaptation level could be caused by the degree to which the product exceeds, meets, or falls short of one's expectation. Post usage ratings of satisfaction appear to be a linear combination of an adaptation level component (expectation) and perceptions of disconfirmation. Subsequent research (Anderson and Sullivan 1993) found that perceived quality and disconfirmation rather than expectation has a direct effect on satisfaction. They also found an asymmetric effect in that negative confirmation has greater impact on satisfaction than positive confirmation.

In this study, we assume that consumers report ratings based on their satisfaction after consumption. That is, everything being equal, a satisfied consumer would post higher ratings than a dissatisfied consumer. We adopt the ECT model as the rationale of our theory development, and posit consumer product evaluation (satisfaction) as a function of experienced quality and expectation disconfirmation. Disconfirmation is defined as the extent to which experienced quality failed to match expected quality. In a general form, Equation [1] shows this relationship.

$$[1]\ SAT_{ijt} = f_1(q_{ijt}) + f_2(q_{ijt} - q_{ijt}^e)$$

Where SAT_{ijt}=satisfaction from product j for consumer i at time t; q_{ijt} =experienced quality of product j for consumer i at time t. q_{ijt}^e =expected quality of product *j* for consumer i at time *t*.

We describe the mechanism of ECT in the context of the reporting of online product ratings as follows. First, consumers form an *a priori expectation* of a specific product or service based on their information about the product prior to a transaction. Online ratings and reviews serve as one major information source from which consumers obtain product information and form expectation about a product, as majority of consumers refer to online ratings and reviews for information about products they are interested in purchasing. Second, after consumption, consumers form perceptions about the *actual* quality level based on their consumption experiences (termed *experienced quality*). Third, consumers compare their post-consumption experienced product quality to their expectation, which could be the same or different from the experienced quality.

When experienced quality exceeds or falls below expectations, satisfaction is based on both experienced quality and the level of disconfirmation. Prior studies have also found the effect of the same level of negative confirmation (disconfirmation) is stronger than the same level of positive confirmation (Anderson and Sullivan 1993), termed as the “asymmetric disconfirmation”. Considering linear function of $f_2(q_{ijt} - q_{ijt}^e)$ in Equation [1], we define α and β as slope of negative confirmation and positive confirmation respectively. Similar to prospect theory (Kahneman et al 1979), perceived level of confirmation $(q_{ijt} - q_{ijt}^e)$ is characterized as an asymmetric function in which α is smaller than β. Negative confirmation (when $q_{ijt} < q_{ijt}^e$) has a higher impact on satisfaction than positive confirmation ($q_{ijt} \geq q_{ijt}^e$). Equation [2] shows this relationship which is illustrated in Figure 1.

$$[2]\ f_2(q_{ijt} - q_{ijt}^e) = \begin{cases} \alpha * abs(q_{ijt} - q_{ijt}^e), if\ q_{ijt} \geq q_{ijt}^e \\ -\beta * abs(q_{ijt} - q_{ijt}^e), if\ q_{ijt} < q_{ijt}^e \end{cases}, \alpha < \beta$$

The experienced quality would be the same regardless of whether consumers get information from sing-dimensional or multi-dimensional rating system, however consumers may form different expectation based on the information they gain from different platforms. And as a result of the difference in expectation, the satisfaction level can be different depending on the disparity between expectation and extent of disconfirmation. Combining Equation [1] and [2], we have Equation [3] which shows this relationship:

$$[3] SAT_{ijt} = \begin{cases} f_1(q_{ijt}) + \alpha * abs(q_{ijt} - q_{ijt}^e), if\ q_{ijt} \geq q_{ijt}^e \\ f_1(q_{ijt}) - \beta * abs(q_{ijt} - q_{ijt}^e), if\ q_{ijt} < q_{ijt}^e \end{cases}, \alpha < \beta$$

Products have different attributes and consumers may have heterogeneous preferences toward different attributes. Consumers form expectations of a product’s utility not only based on information of product quality on different attributes but also on information of whether these attributes fit consumers’ preference, especially for restaurants that have experience attributes that could not be ascertained before consumption. If consumers could obtain this information precisely and completely, they will form precise expectation with small quality uncertainty and fit uncertainty. In this case, we would expect no disconfirmation and satisfaction level will reflect their true experienced quality.

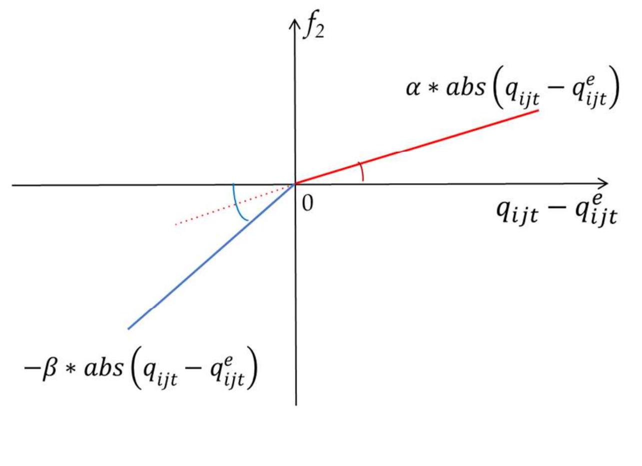

Figure 1. Illustration of the Utility Function

As information in a single-dimensional rating is generally insufficient to reflect multiple dimensional nature of product attributes, it is difficult for consumers to form a precise expectation about the utility. In this case, either disconfirmation occurs, which leads to a lower satisfaction level; or positive confirmation occurs, which leads to a higher satisfaction level. However, conditional on purchase, uncertainty generally leads to a lower decision performance (Hong and Pavlou 2014). Consider the restaurant example, if the rating of a restaurant is one star, it could be interpreted as "the restaurant has really bad food". However, this interpretation could be wrong, making the rating misleading, if not useless. For example it is possible that the restaurant has good food but the consumer who rates it doesn't like the service hence the low rating. It is possible that additional information could be obtained from text reviews (Pavlou and Dimoka 2006) but it takes extra time and effort to read text and try to obtain useful information. This problem may also be solved by extracting different product attributes from review texts (Ghose and Ipeirotis 2010, Archak et al. 2011, Ghose et al. 2011), but it is difficult to translate text comments into ratings, even though one could identify the dimensions that consumers care about.

In a multi-dimensional rating system, a product comprises n-dimensions of attributes, and each attribute has a separate rating. It breaks the single number (i.e., overall rating) down to multiple different dimensions (e.g., food quality, service, ambiance, etc.), thus conveying non-redundant information of the product from a single-dimensional rating system. Consumers could interpret ratings on different dimensions of the product and place different weights on these different dimensions to make their purchasing or consumption decisions. Thus multi-dimensional rating systems could give consumers a comprehensive understanding of the restaurants' attributes and lower both the consumers' quality uncertainty of the restaurants and fit uncertainty to help them pick the restaurant that best fits their preferences. In this way, a multi-dimensional rating system services as a better matching system. Therefore, we would essentially see that in multi-dimensional rating systems, the experienced quality is less likely to deviate from expected quality:

$$[4]\ \mathrm{abs}\left(q_{ijt} - q^e_{ijt}\right)_{multi} < \mathrm{abs}\left(q_{ijt} - q^e_{ijt}\right)_{single}$$

For example, a consumer places high weight on "ambiance" but low weight on "food" might find a restaurant with an overall rating 4, plus ambiance rating 5, food rating 2 more attractive than another restaurant with overall rating 4.5, plus ambiance rating 3.5, food rating 5. Formally, assuming consumers' probability of receiving disconfirmation is $p \sim U(0,1)$, we shall have the following equation:

$$[5]\ SAT_{ijt} = f_1\left(q_{ijt}\right) + \{(1-p)\alpha - p\beta\} * abs\left(q_{ijt} - q^e_{ijt}\right)$$

Therefore, the expectation of consumer rating (based on satisfaction), on average, would be:

$$[6] rating \propto E(SAT) = E\left\{f_1\left(q_{ijt}\right)\right\} - 0.5(\beta - \alpha) * E\left\{abs\left(q_{ijt} - q^e_{ijt}\right)\right\}$$

Combining Equations [4] and [6], we can draw the conclusion that in a multi-dimensional rating system (as opposed to a single-dimensional rating system), as consumers can form more reasonable expectation and pick a restaurant that better fits their need, we should expect consumers more likely to be satisfied, and therefore report a higher ratings.

H1a: The overall rating of multi-dimensional rating system is higher than that of single-dimensional rating system.

Built upon the same rationale, we would expect that consumers could self-select into the restaurants that provide better quality on the dimensions they care about. As a result, prior customers' experiences are also more likely to be replicated, leading to similar ratings. Therefore, we expect:

H1b: The overall rating of multi-dimensional rating system is less likely to deviate from the prior average than that of single-dimensional rating system.

Price effect

Prior research suggest that consumers may use price as a signal of quality before they make purchase decision when they are not certain about the product quality. (Dodds et al. 1991; Grewal 1995; Kirmani and Rao 2000; Mitra 1995; Olson1997; Rao and Monroe 1988, 1989). Consumers may form expectation based on price level in a single-dimensional rating system. It has been observed that there is a positive relationship between ratings and prices in single-dimensional rating system (Li and Hitt 2010) because high quality products usually go for high prices. High price level restaurants are likely to enjoy high ratings while low price level restaurants are likely to suffer low ratings in single-dimensional rating system. A multi-dimensional rating system allows consumers to share quality information along different dimensions, which may better inform later consumers about the quality information. And if such information transfer is efficient, then consumers could find product quality could be ascertained, then they don't have to rely on price level to form expectation. Instead, their expectation are more reasonable based on dimension information which could better fit their preference. And if this is the case, then we should see different effects on high priced and low priced restaurants. The effect is that low price level restaurants will be able to attract customers who have more reasonable expectation of what they may or may not sacrifice because of the low price. It is possible consumers may provide higher ratings which reflect other dimensions of the restaurant except price for low price level restaurants. However, since price doesn't work as a signal of quality, high price level restaurants may not be able to continue enjoying benefit from high price after rating system change, which means that their ratings might not be higher compared to those of single-dimensional systems.

H2: The overall ratings will be higher for low price level restaurant but not for high price restaurants after changing from single-dimensional to multi-dimensional rating system.

Dimension effect

Satisfaction is more sensitive to negative disconfirmation and consumers are motivated to report ratings when they have negative feeling (Engel et al. 1993, Sundaram et al.1998, Hennig-Thurau et al. 2004). As we mention before, consumers have different preferences. Consumers' negative experiences with their preferred product attributes are more likely to evoke negative feelings. In a single-dimensional rating system, consumers are allowed to only report a single rating, hence this rating is more likely to reflect their negative feeling about certain attributes about a product. In a multi-dimensional rating system, consumers report ratings on different dimensions. They may report a low number on the specific attribute they are not satisfied. While on the other dimensions, they could still report positive or objective ratings on other dimensions. Thus, we propose that:

H3a: Ratings in single-dimensional rating systems reflect consumers' experience in the least satisfied dimension in their preferences.

H3b: Ratings in multi-dimensional rating systems reflect consumers' average experience by taking all dimensions into consideration.

Data

To test our hypotheses, we choose restaurants as our context. Restaurants have different dimensions of services (e.g., food, location, etc.) and have attracted a good amount of attention in the academic literature (Luca 2013). We draw upon consumer review data to address our research questions by studying websites with different rating systems. Our empirical analysis utilizes restaurant review data gathered from three leading consumer review websites, *Yelp*.com (*Yelp*) (covering Nov 2004 to April 2013), *OpenTable*.com (*OpenTable*) (covering Nov 2012 to April 2013) and *TripAdvisor*.com (*TripAdvisor*) (covering May 2004 to April 2013). Note that *OpenTable* only provides data of the past six months so our analysis mainly use data from *Yelp* and *TripAdvisor*, while OpenTable data will be used as a robustness check.

Yelp, founded in 2004, contains reviews for a variety of services ranging from restaurants to barbers to dentists, among many others, although most *Yelp* reviews are for restaurants. *Yelp*, among most review websites, provides a single-dimensional five star rating system. Considering website heterogeneity, we pick two websites providing multi-dimensional rating systems, *OpenTable* and *TripAdvisor*, which contain not only the overall ratings but also buyer assessments of the restaurants' dimensional characteristics. The users can rate any restaurant (from 1-5 stars) and they could also rate on different attributes of the restaurant. For instance, *OpenTable* provides overall rating as well as food, service and ambiance ratings. *TripAdvisor* provides dimensional ratings on food, service, atmosphere and value.

In the data collection process, we use three customized web crawlers. To rule out restaurant differences, we obtain exactly the same restaurants from these three websites. Specifically, we first collect the complete set of restaurant data that *OpenTable* displayed for New York City, NY (NYC), which contains 3,000 NYC restaurants, which is the smallest among these three websites. Then we match these restaurants on *Yelp* and *TripAdvisor* by restaurant names, addresses and phone numbers. In total, three websites have 1,201 restaurants in common. We then collect all available reviews for these common restaurants. For each review, we collect the time stamp when the review was reported, the consumer ID and the star rating (an integer between 1 and 5). Note that *TripAdvisor* has both overall ratings and dimension ratings. We also collect the star ratings for each dimension on *OpenTable* and *TripAdvisor*. We calculate the lowest and highest dimensional ratings for each restaurant on *TripAdvisor*. For example, if a restaurant get 5, 5, 4, and 2 on food, service, atmosphere and value separately, then the highest dimensional rating is 5 and the lowest is 2. Besides, we collected the price level of each restaurant from *Yelp*. In total, there are four levels: under $10, $11-$30, $31-$60 and above $61 which accounts 1.4%, 35.5%, 45.9% and 17.1% separately. Considering the percentage, we code price below $60 as low price and price above $61 as high price.Because consumers are not enforced to provide both overall rating and dimensional ratings when they report ratings on *TripAdvisor*, we also calculate the number of dimensional ratings each time.

Note that we exclude the possibility of fake reviews as we are not able to track down fake reviews. Fake reviews will not pose a serious concern for this study because first, the long run effect of fake reviews are likely negligible (Dellarocas 2006); and second, *Yelp* and other websites are spending a huge amount of effect in fighting fake reviews, including legislatures (CNET 2013).

Our key econometric identification strategy hinges on the system change that happened to *TripAdvisor* with regard to its rating system. *TripAdvisor* changed its rating system from single-dimensional to multi-dimensional in January 2009, showing in Figure 2, which provides us a natural experiment setting to test the causal effect of changing online rating system. To study the impact of system change, we focus on reviews one year before January 2009 when the system change happened and one year after January 2010. We choose this time window because it takes time to generate adequate multi-dimensional reviews to exert effect. The effect of the change in rating system does not instantly cause the ratings to increase, it rather takes time for people to go and review, so that information is transformed to later customers, and helps them to make better decisions and finally so that they give out higher reviews for the service. Another reason is one year time window also eliminate any possible effects caused by season. We create a unique dataset by merging data of *TripAdvisor* and *Yelp* by restaurant id. In total, we have 1201 restaurants and 50153 observations.

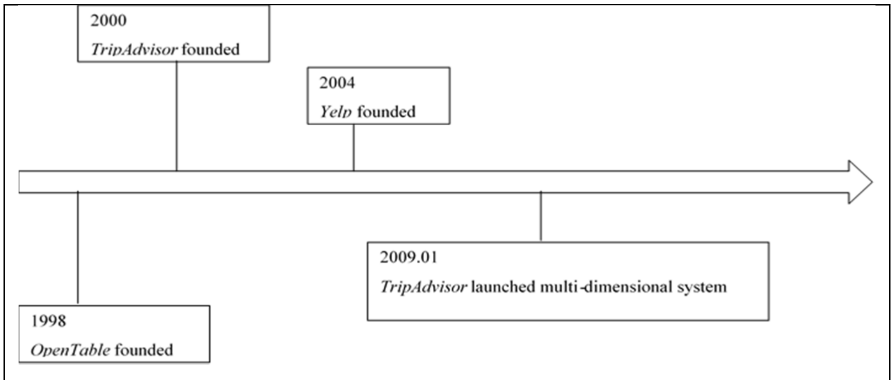

Figure 2. Natural Experiment on *TripAdvisor*

Table 1 reports comparisons between average overall ratings. We report mean ratings of *TripAdvisor* and *Yelp* before and after *TripAdvisor* changed its rating system. We also conduct paired t-tests to compare these mean ratings. We find that the mean rating after system change is much higher than the one before change for *TripAdvisor* while a contrary trend is observed for *Yelp*. This finding is consistent with the view that multi-dimensional rating system help consumers make more effective decisions, therefore higher ratings. We also find that the average ratings of TripAdvisor and *Yelp* before system change are similar, even though they are significantly different. This reminds us that there might be some differences between *TripAdvisor* and *Yelp*. Table 2 presents the number of new ratings each year on these two websites. We could observe there are huge differences of total number of ratings on these websites which we might need to control in our following analysis.

Table 1. Comparisons between Average Overall Ratings

	Pre-change	Post-change	Paired T test
	Mean	Mean	T-statistic
TripAdvisor	3.81	4.10	8.60
Yelp	3.71	3.57	-7.58
T-statistic	3.11	33.10	

Table 2. Number of New Ratings

	2005	2006	2007	2008	2009	2010	2011
TripAdvisor	337	423	2364	5708	3190/2052	4533/3912	13223/10751
Yelp	308	2094	5499	10486	18620	29426	44114

Note: number of new multi-dimensional ratings are presented after slash for *TripAdvisor*

Methodology and Analysis

Difference in difference analysis

As mentioned in section 3, we collect data from *Yelp* and *TripAdvisor*. *Yelp* adopts a single-dimension rating system, while *TripAdvisor* changed its rating system from single-dimension to multi-dimension in January 2009. To identify whether there is any effect of multi-dimensional rating system on the overall ratings, we could compare ratings of *TripAdvisor* before and after system change. However, there might be other reasons causing the change in ratings. For example, the quality of the restaurant might increase or decrease. In this case, we can't tell which factor cause the change in ratings. Here we take the difference in difference approach. We choose the exact same restaurants on *Yelp* as 'control group', therefore rating trend on Yelp for each of these restaurants will serve as a proxy of any change in restaurant quality. Besides, the rating changes at TripAdvisor, after controlling for the rating trend at Yelp, will be due to the change of rating system. Figure 3 demonstrates the relationship.

We summarize this difference in difference approach below:

$$[7] Rating_{it} = \beta_0 + \beta_1 * Change_t + \beta_2 * T_i + \beta_3 * Change_t * T_i + \beta_4 * lognum + \alpha_i + \epsilon_{it}$$

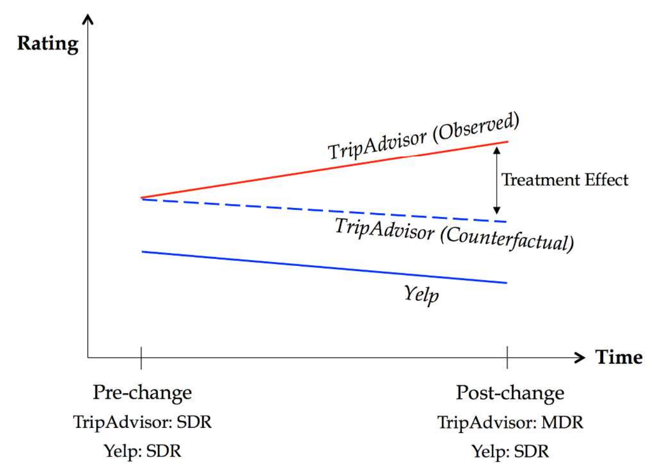

Figure 3. Difference in Difference Analysis

Where i indexes the restaurants and t indexes the time when the rating is made. The dependent variable, $Rating_{it}$, is the consumer rating submitted for restaurant i at time t. $Change_t$ is a time dummy that equals to one if the time period is after the change of rating system, and zero otherwise. Therefore, β_1 measures the before and after rating changes for restaurant i at *Yelp* and is an indication of any quality change of restaurant i. T_i is a dummy that equals to one if the ratings are made on treatment group which is *TripAdvisor*, and zero if on control group which is *Yelp*. β_2 Therefore measures the systematic rating differences across the two websites. The coefficient, β_3, on the interaction term $Change_t$ and T_i measures the difference due to change in rating system, after controlling for restaurant quality changes over time and systematic website differences. α_i denotes restaurant fixed effect. It is possible that there might be other reasons causing the rating difference between *Yelp* and *TripAdvisor* since their average ratings before system change are significantly different. By looking at the website statistics, we find the difference may be caused by total number of ratings. Previous research identified ratings decline over time or sequence. Godes and Silva (2012) find the ratings decrease sequentially because of decreasing similarity among consumers. We include $lognum$,which is the log transformation of the number of previous ratings, to control decreasing trend. Equation [8] tests whether there are significant difference between *Yelp* and *TripAdvisor* before system change. Equation [9] tests whether there are significant difference of *Yelp* before and after system change.

$$[8] Rating_{it} = \beta_0 + \beta_1 * T_i + \beta_2 * lognum + \alpha_i + \epsilon_{it}$$

$$[9] Rating_{it} = \beta_0 + \beta_1 * Change_t + \beta_2 * lognum + \alpha_i + \epsilon_{it}$$

To test H1b, we relate Deviation of ratings to the nominal sequence value of the rating at time t. Rating deviation of restaurant i at time t is measured as the absolute difference between rating made by consumer at time t and previous observed rating. We compute previous observed rating as the average of all ratings made before time t. Since the dataset consists of different restaurants, we include restaurant fixed effects α_i as controls in the analysis. β_1 measures the relationship between deviation of current rating from previous observed ratings and sequence. A positive β_1 means deviation from previous observed rating increase with rating sequence, while a negative β_1 means deviation from previous observed rating decrease with rating sequence, which indicate convergence of ratings.

$$[10] Deviation_{it} = |r_{it} - \mu_{it-1}|$$

$$[11] Deviation_{it|SD} = \beta_0 + \beta_1 * Sequence + \alpha_i + \epsilon_{it}$$

$$[12] Deviation_{it|MD} = \beta_0 + \beta_1 * Sequence + \alpha_i + \epsilon_{it}$$

We also directly compare the deviation effect between single-dimensional and multi-dimensional using equation [13] where β_3 captures the difference of rating deviation with rating sequence between *Yelp* and *TripAdvisor*.

$$[13] Deviation_{it} = \beta_0 + \beta_1 * Sequence + \beta_2 * T_i + \beta_3 * Sequence * T_i + \alpha_i + \epsilon_{it}$$

Results

Table 3 shows the results of equation [8] and [9] which aim to investigate whether there are any systematic differences between *Yelp* and *TripAdvisor*. Equation [8] use a sub-dataset of ratings before system change on the two websites and the results are shown on the first column. The negative coefficient of $lognum$ shows that there is a decreasing trend of ratings on both websites. The insignificant coefficient of T_i shows that there is no systematic difference between *Yelp* and *TripAdvisor* before system change after controlling for the downward trend of ratings. Equation [9] use a sub-dataset of *Yelp* before and after system change and the results are shown on the second column. We could still observe a downward trend. Besides, the insignificant coefficient of $Change_t$ shows that there is no significant difference of *Yelp* before and after rating system change. The results show that after controlling for the downward trend of ratings, *Yelp* and *TripAdvisor* are comparable. We don't have to consider other factors which might caught any systematic differences between these two websites except for rating system change.

Table 3. Websites Difference Estimation

	(1) *Rating*	(2) *Rating*
$lognum$	-0.099***(0.024)	-0.078***(0.022)
T_i (Comparison between *Yelp* and *TripAdvisor* before system change)	-0.006(0.031)	
$Change_t$ (Comparison of *Yelp* before and after system change)		0.036(0.028)
_cons	4.1***(0.0882)	4.0***(0.0769)
N	16194	39912
Restaurant Fixed Effects	Yes	Yes

Note: *** p<0.001, p<0.01, * p<0.05; Robust standard errors are in parentheses.

Table 4 presents the estimation results for difference in difference analysis for equation [7]. Column (1) of table 4 presents the results for a regression in which restaurant variables are not included. The significant positive coefficients of $Change_t$ indicate that the change of rating system from single-dimensional to multi-dimensional significantly increase ratings by 0.176. The restaurant results increase by 0.176 on average as a result of rating system change. The increase of ratings suggest that consumers are able to form rational expectation based on the information gathering from multi-dimensional rating system which could better match their preference. H1a is supported. The results holds when we consider restaurant fixed effects in column (2).

Table 4. Difference in Difference Analysis		
	(1) *Rating*	(2) *Rating*
$\boldsymbol{Change_t}$	-0.125***(0.013)	-0.016(0.026)
$\boldsymbol{T_i}$	0.205***(0.017)	0.068*(0.028)
$\boldsymbol{Change_t{*}T_i}$	0.176***(0.026)	0.164***(0.034)
lognum	0.082***(0.005)	-0.040*(0.016)
_cons	3.4***(0.019)	3.9***(0.056)
N	50153	50153
Restaurant Fixed Effects		Yes

Note: *** p<0.001, p<0.01, * p<0.05; Robust standard errors are in parentheses.

Deviation

We present the preliminary results in Table 5. We use all data after January 2009 when *TripAdvisor* changed its rating system. To control for any website specific effect, we also report the results of *OpenTable*. Column (1) to (3) use data of *Yelp*, *TripAdvisor* and *OpenTable* seperately. Column (4) use the combined data of *Yelp* and *TripAdvisor*. We also control for restaurant fixed effects to get unbiased results. The coefficients are significantly positive for *Yelp* and negative for *OpenTable* and *TripAdvisor*. Considering the differences might be resulted from consumer pools, we are glad to see the coefficients are of the same sign for both *Opentable* and *Tripadvisor*.

Table 5. Fixed Effects Estimation (DV=Difference from Mean Rating)				
	(1) *Yelp*	(2) *TripAdvisor*	(3) *OpenTable*	(4) *Yelp and TripAdvisor*
Sequence	0.00014***	-0.00031***	-0.00020***	0.000078***
$\boldsymbol{T_i}$	-	-	-	-0.025***
*Sequence**$\boldsymbol{T_i}$	-	-	-	-0.00018***
_cons	0.80***	0.84***	0.86***	0.82***
Restaurant Fixed Effects	Yes	Yes	Yes	Yes

Note: *** p<0.001, p<0.01, * p<0.05; robust standard errors are in parentheses.

The results suggest that with the increasing of the number of ratings, the absolute difference between previous average rating and the next rating increase in single-dimensional rating system and decrease in multi-dimensional-dimensional rating system. Column (4) shows the difference between single-dimensional rating system and multi-dimensional rating system is significant. Deviation from previous ratings is smaller for multi-dimensional ratings than single-dimensional ratings. The results also suggest ratings are converging in multi-dimensional system. H1b is supported.

Price effect

Table 6 redefines different groups of restaurants and extend our analysis to explore whether the system change effect differ across restaurants with different price level. We could observe a positive significant effect of system change in low price level restaurant. The effect is even larger compared to result in Table 4. However, the effect is not significant for restaurants with high price level. In another word, restaurants with lower price level benefit more from rating system change. The results are consistent with Li and Hitt (2010) which suggest in single-dimensional rating system, with insufficient information, consumers would perceive price level as a signal for restaurant quality. While in multidimensional rating system, consumers could get more information from the dimension ratings of the restaurant, in this case, they could provide more rational ratings. H2 is supported.

Table 6. Difference in Difference Analysis (Price Effect)

	(1) Low Priced Restaurants	(2) High Priced Restaurants
	Rating	*Rating*
$\boldsymbol{Change_t}$	-0.027(0.028)	-0.009(0.067)
$\boldsymbol{T_i}$	0.101**(0.033)	-0.002(0.052)
$\boldsymbol{Change_t * T_i}$	0.186***(0.040)	0.100(0.067)
lognum	-0.035*(0.018)	-0.033 (0.039)
_cons	3.8***(0.06)	4.1***(0.15)
N	40921	9061
Restaurant Fixed Effects		yes

Note: *** p<0.001, p<0.01, * p<0.05; Robust standard errors are in parentheses.

Since *TripAdvisor* provides dimension rating of value, we also want to investigate whether value rating affect price effect hypothesis. Table 7 demonstrates the correlation between price level and value ratings on multi-dimensional rating system. The negative correlation suggests that value dimension rating on *TripAdvisor* doesn't reflect the price level of the restaurant. Instead, it shows how the price level fits the restaurant quality. In this case, value rating on multi-dimensional rating system doesn't affect price effect hypothesis.

Table 7. Correlation between Price Level and Value Rating

	Price
Value rating on *TripAdvisor*	-0.08***

Dimension effect

Figure 4 presents the mean overall rating of *Yelp* and *TripAdvisor* using all data after 2009 when *TripAdvisor* changed its rating system. It also presents mean of the highest and lowest rating across four dimensions for each restaurant on *TripAdvisor*. It is evident from the figure that the overall rating of multi-dimensional rating system of *TripAdvisor* (the third column) lies approximately between the lowest (the first column) and highest ratings of different dimensions (the fourth column). While the overall rating in the single-dimensional rating system of *Yelp* (the second column) closely matches the lowest dimension rating in the multi-dimensional rating system of *TripAdvisor*.

Figure 4 also shows the box plot of ratings comparing *Yelp*, *TripAdvisor*, and the lowest and highest dimension rating of *TripAdvisor*. The first two boxes present the distribution of the lowest dimension rating of *TripAdvisor* and average rating of *Yelp*. Although the mean is significantly different, we could observe that these two boxes overlap to great extent and the distributions are quite similar to each other. Besides, they are not overlapped with the last two boxes which present the distribution of the highest dimension rating of *TripAdvisor* and average rating of *TripAdvisor* respectively. Average rating of *TripAdvisor* are totally different from that of *Yelp*. Besides, average rating of *TripAdvisor* distributes between its lowest and highest dimension ratings. The finding is very interesting, as it indicates that when consumers can only provide a single rating, then that single rating tends to reflect consumers' least satisfied dimension, which is consistent with previous research (Engel et al. 1993, Sundaram et al.1998, Hennig-Thurau et al. 2004) that consumers are motivated to report ratings when they have negative feeling. On the other hand, when consumers can report separate ratings for different dimensions, then their overall rating tends to reflect consumers' average experience, taking into account all dimensions. H3a and H3b are supported.

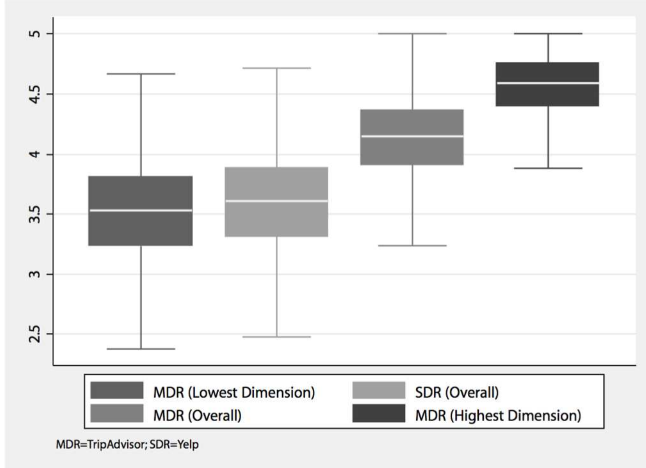

Figure 4. Average Rating Distribution

Discussion

Key findings

Our study seeks to extend limited understanding of the importance of different designs of online rating systems. Our results, based on data from leading online review platforms, first show that ratings become higher after the adoption of a multi-dimensional system, compared with a single-dimensional rating system that did not switch to a multi-dimensional system. This finding provides evidence that consumers form more reasonable expectations and make more effective decisions from multi-dimensional ratings and are therefore more satisfied after consumption.

Second, our results indicate that restaurants with lower price level benefit more changing from single-dimensional to multi-dimensional rating system because consumers of single-dimensional rating system would perceive price level as a signal of quality, however consumers in multi-dimension rating system consumers don't could easily get more comprehensive information and didn't have to rate relying on price.

Third, another interesting finding emerged from our research that when consumers are only allowed to report one single rating, they tend to report the rating based on the "least" satisfied aspect in their consumption, however, when they can report separate ratings on different dimensions, then they will be more objective and the overall rating would be based on experiences on all dimensions.

In sum, our findings suggest that there are benefits by switching from single-dimensional to multi-dimensional ratings, especially for experience goods. Consumers are more likely to form rational expectations. Ratings are increasing with decreasing marginal effect and finally convergent. Information is transferred among consumers more effectively.

Theoretical Implications

Our model relates product information that consumers could gain from online rating system to product uncertainty, which is further integrated to consumer expectation and satisfaction, based on the expectation confirmation theory. To our knowledge, this paper is the first study that directly addresses whether multi-dimensional ratings facilitate information transfer efficiency and whether multi-dimensional ratings provide net benefits for consumers. We extend prior work on dynamic effects of ratings (Li and Hitt 2008, Godes and Silva 2012, Moe and Schweidel 2012) to find downward trend of single-dimensional ratings and argue that a plausible explanation is consumer heterogeneity. We show that such downward trend (consumer become even less satisfied over time with more information) can be corrected by using multi-dimensional rating system. Our results show an upward and convergent trend of multi-dimensional ratings, which indicate that, after adopting a multi-dimensional rating system, consumers' preferences are better matched to the restaurants' attributes as information from multi-dimensional rating systems is efficiently transferred to them. We also extend limited understanding of the importance of different designs of online rating systems called for many IS scholars (Archak et al. 2011, Ghose and Ipeirotis 2011). This study extends extant research on how IT-enabled technologies could reduce consumer product uncertainty (Dimoka et al. 2012, Kwark et al. 2014)

Practical Implications

First, the results from this study inform practitioners about whether adopting a multi-dimensional rating system can improve online product review performance and also provide insights on effective design of informative rating systems. Review Websites are suggested to consider adopting a multi-dimensional rating system to provides more accurate and complete information to consumers. Our results also suggest that system change effect depends on the number of multi-dimension ratings as we observed cross-restaurant variances after the system change. Therefore, it is in the best interest of review websites to attract more consumers to provide dimension ratings other than only provide the overall ratings. Besides, our results suggest restaurants with lower price level would benefit more than restaurant with higher price level. One suggestion is that restaurants with lower price level to encourage (or even incentivize) their customers to provide multi-dimensional ratings.

Limitation and Future research

First, this research directly examines how multi-dimensional rating system can enhance information transfer efficiency through a better matching of consumer preferences to product attributes, in the context of restaurant reviews. Although sufficient field evidence is provided for the case of adopting a multi-dimensional rating system, one caveat should be made that the results may not generalized to other types of products, such as search goods. It will be interesting to look at whether different performance effects will be observed for different types of products when a multi-dimensional rating system is introduced, e.g., search, experience, and credence goods. Second, to the extent that multi-dimensional ratings help reduce uncertainty, as is evident from our results, we predict that there is positive relationship between multi-dimensional ratings and sales. Therefore, a natural extension of our work is to examine relationships between multi-dimensional ratings to sales or other performance data. Previous research has tried to link single-dimensional ratings to firm revenue and stock market (e.g., Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Dellarocas et al. 2007, Duan et al. 2008, Forman et al. 2008, Moe 2009). Similar empirical analyses could be performed to examine multi-dimensional rating systems. Third, it is possible that additional information could be obtained from text reviews (Pavlou and Dimoka 2006) or extracting different product attributes from review texts (Ghose and Ipeirotis 2010, Archak et al. 2011, Ghose et al. 2011),which we don't control in this study, but it takes extra time and effort to read text and try to obtain useful information. Consumers could get a basic understanding of different dimensions of the restaurant through average dimension ratings displayed on the restaurant home page. However, it may take several times as long to get information on a single-dimensional rating system by reading almost all previous reviews.

Conclusion

Based on a quasi-experimental difference-in-difference framework, our study utilizes a novel data set combining data from three leading online review websites to investigate the value of adopting a multi-dimensional rating system from a single-dimensional rating system, in terms of information transfer efficiency. Our results provide support that multi-dimensional rating systems enhance information transfer efficiency and lead to more effective purchasing decisions and happier customers. Restaurants with lower price level benefit more from rating system change. Consumers tend to report ratings to express their strong negative feelings in single-dimensional system and average experience in multi-dimension system. Ratings are convergent in multi-dimensional rating system. Given the societal importance of online word of mouth and online product review systems, our study serves as an important first step towards establishing a causal effect of adopting a multi-dimensional rating system.

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