Matching Consumer Preferences with Product Attributes: The Value of Multi-dimensional Online Word of Mouth Systems

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Abstract

Online reviews and ratings help consumers learn more about products. However, mixed findings have been found regarding the effects of ratings on consumer decision-making. Such lack of effect may be due to the limitation of single-dimensional ratings in transferring quality information. Since quality often comprises of multiple dimensions, some scholars have urged for multi-dimensional rating systems as a way to better convey quality information. This paper directly addresses whether, and to what extent, multi-dimensional rating systems enhances information transfer efficiency, and empirically quantify 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 www.TripAdvisor.com (*TripAdvsior*) when it changed its rating system from single dimension to multi-dimension in 2009. To control for any unobserved quality change over time at the restaurant level, we also obtained ratings data on the same set of restaurants from Yelp. This allows us to identify the causal effect with a difference-in-difference approach. Our results show that ratings tend to be more dispersed and are trending down in single-dimensional rating system compared to multi-dimensional ratings, providing support that consumers form more accurate expectation from multi-dimensional ratings and are therefore less likely to be disappointed (which would result in lower ratings) or "surprised" (which would lead to higher dispersion of ratings). We further investigate the source of difference in information transfer efficiency by exploring how consumers map ratings between single dimensional and multi-dimensional rating systems. Interestingly, we found that single dimensional ratings tend to reflect consumers' experience in the least satisfied dimension. However, in the multi-dimensional rating system, the ratings reflect consumers' overall experience. These results demonstrate the information value of multi-dimensional ratings. Our study provides important implications for a better design of online rating systems to help consumers match their preferences with product/service attributes.

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

1. Introduction

The substantial increase of online word of mouth (WOM) in the form of online product reviews and ratings 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 (usually on a discrete interval scale of 1-5) of the product, in addition to 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 follows a single-dimensional system (e.g., *Amazon*.com, *Yelp*.com, etc.), with a few exceptions that acquire and report ratings in different dimensions (*TripAdvisor*.com, *OpenTable*.com). Prior studies have examined the impact of product ratings on sales, and mixed findings have been reported (Chevalier and Mayzlin

2006, Duan et al. 2008). The mixed findings question the assumption that ratings reveal product qualities. Because single-dimensional ratings ignore consumers' heterogeneity in their multi-dimensional preferences (Godes and Silva 2012, Moe and Schweidel 2012), the usefulness of single-dimensional rating system might be questionable (at least for some products, such as books). 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). Given the potential multi-dimensional nature of consumer preferences for many experience products, it is difficult for consumers' idiosyncratic preferences to be matched onto a single numerical rating in such single-dimensional rating systems. Multi-dimensional system has been proposed and implemented in some websites to address this challenge as it presumably allows consumers to provide different ratings on different dimensions of the product/service that would reflect both quality and preference attributes, and consumers who consume the information would be able to determine what they would gain or may have to compromise, given same overall ratings. As a result, it is likely that multi-dimensional rating system could facilitate the matching process. The rationale behind this claim is that multi-dimensional rating system facilitates more efficient information transfer among consumers by reflecting their experiences onto different dimensions of quality or preference, so that it is easier for consumers to better choose a product that they are more likely to enjoy. Notably, given this important variation in the design of online rating systems, there is a dearth of empirical evidence establishing the superiority of either design (single- or multi-dimensional rating systems).

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 the multi-dimensional rating system. 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. When such information transfer is efficient, consumers exposed to multi-dimensional rating systems prior to consumption are likely to make more informed decisions and are therefore more satisfied with their purchases. On the other hand, the text reviews of the single-dimensional rating system could serve the same purpose as consumers are able to express their evaluations of different dimensions in their reviews, therefore, decreasing the value and need of multi-dimensional ratings. Moreover, even if we believe that multi-dimensional ratings contain more information, there are also reasons to believe that more information does not 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 (Simon 1982), it is not clear whether providing additional multi-dimensional ratings will provide a net increase in decision performance over a single rating. In addition, in terms of implementation, re-designing a single-dimensional rating system into a multi-dimensional system is costly. And consumers might also find it time-consuming to rate different dimensions given the extra effort, thus reducing the content generation quality. In sum, there is considerable value to examine whether a multi-dimensional system makes information transfer easier among consumers.

The goal of this research is to 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?

We examine the efficiency of information transfer by observing the dynamics of ratings over time in single dimensional vs. multi-dimensional rating systems. When information transfer is efficient in a rating system, consumers are more able to learn from the ratings and reviews and be able to distinguish between different similar products and 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 conveyed in the ratings and reviews. As a consequence, we should observe less dissatisfied consumers and less variation in ratings over time when information transfer is efficient. We find evidence that multi-dimensional rating systems enhance information transfer efficiency by comparing the rating trends before and after the system change in TripAdvisor (TripAdvisor changes from single dimensional to multi-dimensional in 2009), and across TripAdvisor (multi-dimensional) and Yelp (single dimensional).

We also examine the role of *price* in single and multi-dimensional rating systems. Price has long been used as a cue of quality, when quality cannot be ascertained before purchase (Dodds et al. 1991; Grewal 1995; Kirmani and Rao 2000; Mitra 1995; Rao and Monroe 1988, 1989). However, although high price may signal high qualities in all dimensions for high-priced restaurants, low price doesn't necessarily suggest low qualities in all dimensions. Unfortunately, single dimensional rating system makes it more difficult to transfer the information about which dimension a low priced restaurant suffers that earned it the low rating, and why a low priced restaurant has a low rating is subject to consumers' own interpretation, which may not be correct. A multi-dimensional rating system, on the other hand, makes it possible to convey that information to consumers so consumers have a better expectation of which dimensions they may have to compromise and which they don't have to for the low price. Since quality and fit uncertain is in general higher for low priced restaurants than for high-priced restaurants, we expect low priced restaurants to benefit more from multi-dimensional ratings than high priced restaurants because dimensional information enables consumers to better select restaurants according to their heterogeneous weights on the different dimensions.

Besides comparing the relative performance of single versus multi-dimensional rating systems, we are also interested in several other empirical questions. Anderson (1998) proposed that consumers are more likely to engage in word-of-mouth when they have extreme opinions. Given products/services usually have different dimensions (e.g. location, service and food quality in a restaurant setting), consumers may form extreme opinions on one dimension or different dimensions. It is interesting to understand *how consumers map their dimension opinions into the 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.

To address our research questions, we collect data from two leading restaurant review websites (*Yelp* and *TripAdvisor*). We sample 1207 restaurants in New York City, and obtain reviews for these restaurants on these two 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*, which changed its rating system from single-dimensional to multi-dimensional in January, 2009. In the meantime, a similar review website, *Yelp*, did not make such a change and maintains a single dimensional rating system. 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 0.154. Notably, the increase in ratings is even stronger as more dimensional ratings are accumulated. 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, suggesting that consumers' consumption reflect their expectation. 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 as identified 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 reduce both quality uncertainty and fit uncertainty, 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 presents the data, empirical methodologies and results of econometric analyses. In Section 5, we discuss the results, managerial and theoretical implications and future research with a conclusion of section 8.

2. 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. Single-dimension rating system ignores consumers' heterogeneity and fit between products and consumers, resulting in a biased rating system. Li and Hitt (2008) found self-selection problem using Amazon book reviews data by showing that online reviews tend to trend downward overtime. Their explanation is those who have the strongest preferences for the book may post higher ratings in the early stage. Godes and Silva (2012) investigated the impact of the sequence of ratings beyond the temporal effect. They found the ratings decrease sequentially. They argued that the increasing difficulty in diagnosticity assessment and decreasing similarity among consumers over the sequence could be the complimentary explanation. Since aggregating or averaging consumer preferences is usually not meaningful (Hong et al. 2012), this may partly explain the mixed findings of the relationship between review valence and sales (Duan et al. 2008). 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) took rating heterogeneity into account and estimated the relative effect of product attributes and brand names on the overall evaluation of the products. Ghose et al. (2012)

estimated consumer demand and various product attributes using hotel reservation data and consumer-generated reviews, and then they proposed a new ranking system which could reflect consumers' multidimensional preferences for products. Ghose and Ipeirotis (2011) and Archak et al. (2011) examined 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 differently. In sum, consumers do consider information on different dimensions of a product before consumption. When the rating system is single-dimensional, consumers might look for information on different dimensions of a product from the text reviews. Notably, there is no research directly examine the role of multi-dimensional rating systems on facilitating the matching of consumer preferences with product attributes. In later sections, we will provide theoretical discussions and empirical evidence supporting the view that a multi-dimensional rating system significantly enhances information transfer efficiency and leads to more satisfied customers and more consensus of quality information.

3. Hypothesis Development

The focus of this study is on examining whether a multi-dimensional rating system increases information transfer efficiency. In this section, we measure the effect through comparing the overall ratings besides the rating convergence trend for the identical products on two websites which adopt single and multi-dimensional rating system respectively. We leverage Expectation-confirmation theory (ECT) to help theorize the effect of a multi-dimensional rating system on information transfer efficiency and in turn, consumer satisfaction. We also focus on price which can influence the effect and consumers' evaluation of different dimensions.

3.1. Multi-dimensional System and Consumer Satisfaction

ECT is widely used in the information systems and marketing literature to understand system adoption (Bhattacherjee 2001, Brown et.al 2012, Lin et al. 2012, Brown et al. 2014, Diehl and Poynor 2010, Venkatesh and Goyal 2010) 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. Therefore, post consumption ratings of satisfaction appear to be a linear combination of expectation and disconfirmation. Subsequent research (Anderson and Sullivan 1993) found that perceived quality and disconfirmation rather than expectation has a direct effect on satisfaction. They also report an asymmetric effect in that negative confirmation has greater impact on satisfaction than positive confirmation.

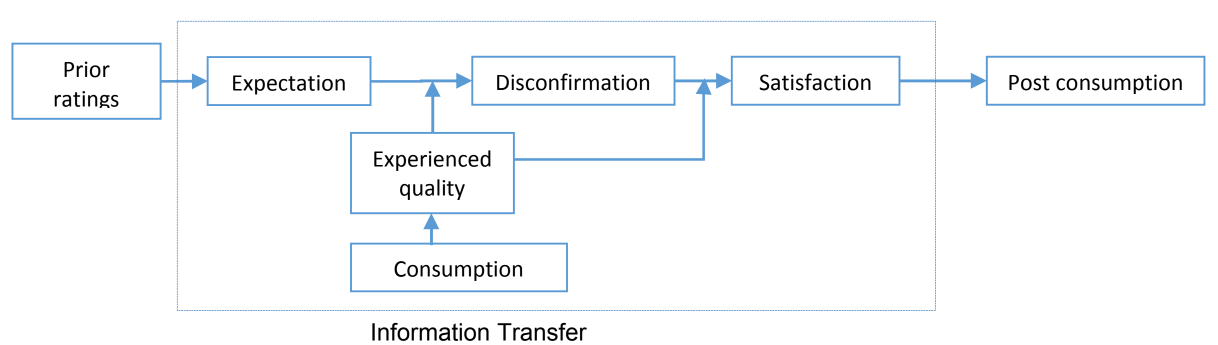

Figure 1. Information Transfer Model

We adopt the ECT model from Anderson and Sullivan 1993 as the rationale of our theory development. In this study, we recognize that ratings serve dual roles, as input and as output of an information transfer and consumption process. For a consumer who searches for information, prior ratings by other consumers serve as an input based upon which such consumer can form expectation of product utility, and this same consumer can report her own rating to reflect her own consumption experience, therefore, this rating can be considered as the "output" of an information consumption process. When the output rating matches input ratings, it suggest that expectation is realistic and therefore confirmed. On the other hand, when output rating differ from input ratings, it suggests that expectation is unrealistic, that is, information is not corrected transferred therefore, and expectation is not confirmed. By observing this input-output dynamics over time, we get an assessment of information transfer efficiency. We model this information input-output process below:

We assume that consumers' report ratings are based on their satisfaction after consumption. That is, everything being equal, a satisfied consumer would post higher ratings than a dissatisfied consumer. Satisfaction is a function of experienced quality and expectation (dis)confirmation. Consumers form *a priori* expectation of a specific product or service based on their information about the product. Online ratings and reviews serve as one major information source from which consumers obtain product information and form expectation about a product. After consumption, consumers form perceptions about the actual quality level based on their consumption experiences (termed experienced quality). And then, consumers compare their experienced product quality to their expectation, which could be the same or different from the expected quality. When experienced quality exceeds or falls below expectations, satisfaction is based on both experienced quality and the level of 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 (Anderson and Sullivan 1993).

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

Where SAT_{it} equals to satisfaction of product i at time t; q_{ijt} denotes experienced quality of product i at time t. q_{it}^{e} denotes expected quality of product i at time t.

Prior studies have also found the effect 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 $f_2(q_{it} - q_{it}^{e})$ in Equation[1], we define α and β as the slope of negative confirmation and positive confirmation respectively. Similar to prospect theory (Kahneman et al 1979), perceived level of confirmation $(q_{it} - q_{it}^{e})$ is characterized as an asymmetric function in which α is smaller than β. Negative confirmation (when $q_{it} < q_{it}^{e}$) has a higher impact on satisfaction than positive confirmation $(q_{it} \geq q_{it}^{e})$. Equation [2] shows this relationship which is illustrated in Figure 2.

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

The experienced quality would be the same regardless of expectation, however consumers may form different expectation based on the information from different platforms. 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:

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

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 products 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 because experienced quality is more likely to reflect expected quality.

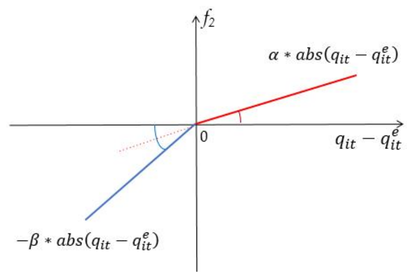

Figure 2. Illustration of the Utility Function

As information in a single-dimensional rating system is generally insufficient to reflect the 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 a 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. For example, it is possible that the restaurant has good food, but the consumer who rates it doesn’t like the service provided, 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 the text and 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] $\text{abs}(q_{it} - q_{it}^{e})_{MD} < \text{abs}(q_{it} - q_{it}^{e})_{SD}$

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

[5] $SAT_{it} = f_1(q_{it}) + \{(1-p)\alpha - p\beta\} * abs(q_{it} - q_{it}^{e})$

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

[6]$rating \propto E(SAT) = E\{f_1(q_{it})\} - 0.5(\beta - \alpha) * E\{abs(q_{it} - q_{it}^{e})\}$

Combining Equations [4] and [6], we can get that

$$[7] rating_{MD} > rating_{SD}$$

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 rating.

H1: 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:

H2: The overall rating of multi-dimensional rating system is less likely to deviate from the prior average than that of single-dimensional rating system.

3.2. Moderating Effect of Price

Prior research suggests that consumers may use price as a signal of quality before they make purchase decisions 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). 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. However, although high price may signal high qualities in all dimensions for high-priced restaurants, low price doesn't necessarily suggest low qualities in all dimensions. Unfortunately, single dimensional rating system makes it more difficult to transfer the information about which dimension a low priced restaurant suffers that earned it the low rating, and why a low priced restaurant has a low rating is subject to consumers' own interpretation, which may not be correct. A multi-dimensional rating system, on the other hand, makes it possible to convey that information to consumers so consumers have a better expectation of which dimensions they may have to compromise and which they don't have to for the low price. This dimensional information enables better selection of restaurants according to consumers' heterogeneous weights on the different dimensions. Since quality and fit uncertain is in general higher for low priced restaurants than for high-priced restaurants, we expect low priced restaurants to benefit more from multi-dimensional ratings than high priced restaurants.

H3: The increase in ratings will be higher for low price level restaurants but not for high price restaurants after changing from single-dimensional to multi-dimensional rating system.

3.3. Dimension Effect

The literature has established that satisfaction is more sensitive to negative disconfirmation, and consumers are motivated to report ratings when they have negative feelings (Engel et al. 1993, Sundaram et al.1998, Hennig-Thurau et al. 2004). As we have mentioned 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 lower 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. Because consumers are able to reflect their experiences on different dimensions, we expect the overall ratings will then be more reflective of their objective overall consumption experience. Thus, we propose that:

H4a: Ratings in single-dimensional rating systems reflect consumers' experience in the least satisfied dimension in their preferences.

H4b: Ratings in multi-dimensional rating systems reflect consumers' average experience by taking all dimensions into consideration.

4. Research Setting

4.1. Data

We draw upon consumer review data to address our research questions by studying websites with different rating systems in the context of restaurants. 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). 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* is used as a list to draw common restaurants across the three websites and its data is also used in the robustness check.

Yelp, founded in 2004, contains reviews for a variety of services ranging from restaurants to barbers to dentists, most reviews on *Yelp* are for restaurants. Like most review websites, *Yelp* provides a single-dimensional five star rating system. *TripAdvisor* contains 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, such as 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 across the three review sites. Specifically, we first collect the complete set of restaurant data that *OpenTable* displays for New York City, NY (NYC), which contains 3,000 NYC restaurants, which is the smallest set 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 1,207 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 collect 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 $30 as low price and price above $31 as high price. Note that even though *TripAdvisor* transforms from single dimensional to multi-dimensional rating system, consumers are not enforced to provide dimensional ratings when they report ratings on *TripAdvisor*, that is, they could still just report an overall rating as in a single-dimensional rating system. Because of this, we also calculate the number of dimensional ratings at 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, these review 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, which provides us a natural experiment setting to test the causal effect of the online rating system change. 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 effects. 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 eliminates 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.

4.2 Difference in Difference (DID) Framework

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 its system change. However, there might be other factors causing the change in ratings. For example, the quality of the restaurants might increase or decrease. In this case, we can't tell which factors cause the change in ratings. Here we utilize 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. Any factors related to restaurant quality changed will be controlled. 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.

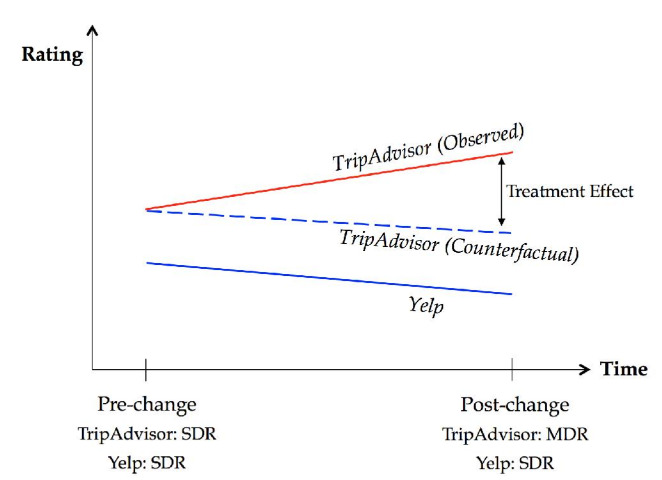

Figure 3. **Difference in Difference Analysis**

Although we obtain the exact same restaurants on the two websites, it is not sure that whether there are any systematically differences between *TripAdvisor* and *Yelp.* Table 1 reports comparisons between average overall ratings of the two websites. 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 the change for *TripAdvisor* while a contrary trend is observed for *Yelp.* This finding is consistent with the view that multi-dimensional rating system helps consumers make more effective decisions, therefore higher ratings. We also find that the average ratings of *TripAdvisor* and *Yelp* before system change are in the same ball park, but the difference significantly enlarged after *TripAdvisor's* system change.

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*

5. Econometric Identification

5.1. Website difference

To rule out any systematic difference due to review websites, we examine the ratings of same restaurants across the two websites before the system change. We include $logn_r$,which is the log transformation of the number of previous overall ratings, to control the decreasing trend that has been observed at Yelp and in many prior studies. Equation [8] tests whether there are significant differences between *Yelp* and *TripAdvisor* before system change. Equation [9] tests whether there are significant differences of *Yelp* before and after system change.

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

$$[9] Rating_{ikt} = \beta_0 + \beta_1 * MD_t + \beta_2 * logn_r + \alpha_i + \epsilon_{ikt}$$

Where i indexes the restaurants, t indexes the time when the rating is made and k indexes the website. The dependent variable, $Rating_{ikt}$, is the consumer rating submitted for restaurant i at time t on website k. MD_t is a time dummy that equals to one if the time period is after the change of rating system, and zero otherwise. 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*. α_i denotes restaurant fixed effect.

5.2. DID Model: Main effect of the rating system change

We summarize difference in difference approach below:

$$[10] Rating_{ikt} = \beta_1 + \beta_2 * T_i + \beta_3 * MD_t * T_i + \beta_4 * logn_r + \alpha_i + \epsilon_{ikt}$$

β_2 measures the before and after rating changes for restaurant i at *Yelp* and is an indication of any quality change of restaurant i. The coefficient, β_3, on the interaction term MD_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.

5.3. Deviation Model

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 ratings 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 ratings increase with rating sequence, while a negative β_1 means deviation from previous observed rating decrease with rating sequence, which indicate the convergence of ratings.

$$[11] Deviation_{it} = |r_{it} - \mu_{it-1}|$$

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

$$[13] Deviation_{it|TripAdvisor} = \beta_0 + \beta_1 * Sequence + \alpha_i + \epsilon_{it}$$

We also directly compare the deviation effect between single-dimensional and multi-dimensional using equation [14] where β_3 captures the difference of rating deviation with rating sequence between *Yelp* and *TripAdvisor*.

$$[14] Deviation_{it} = \beta_0 + \beta_1 * Sequence + \beta_2 * T_i + \beta_3 * Sequence * T_i + \alpha_i + \epsilon_{it}$$

6. Results

6.1 Results for website difference

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 all ratings before the system change on the two websites and the results are shown in the first column. The negative coefficient of $lognum$ shows that there is a decreasing trend of ratings on both websites. The insignificant coefficient of MD_t shows that there is no systematic difference between *Yelp* and *TripAdvisor* before the system change after controlling for the downward trend of ratings. Equation [9] use ratings data of *Yelp* before and after system change and the results are shown in the second column. We could still observe a downward trend. Besides, the insignificant coefficient of T_i 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.

Table 3. Websites Difference

	(1) *Rating*	(2) *Rating*
$logn_r$	-0.099***(0.024)	-0.078***(0.022)
T_i (Comparison between *Yelp* and *TripAdvisor* before system change)	-0.006(0.031)	-
MD_t (Comparison of *Yelp* before and after system change)	-	0.036(0.028)
N	16194	39912
Restaurant Fixed Effects	Yes	Yes

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

6.2 DID Results for overall ratings

Table 4 presents the estimation results of difference in difference analysis for equation [9]. Column (1) presents the results for a regression including restaurants fixed effect. The significant positive coefficient of MD_t*T_i indicates that the change of rating system from single-dimensional to multi-dimensional significantly increase ratings by 0.154. That is, the restaurant ratings increase by 0.154 on average as a result of rating system change. The increase of ratings suggests that consumers are "happier" in the sense that they are able to form rational expectation based on the information gathered from multi-dimensional rating system which could better match their preference. H1 is supported.

Column (2) and Column (3) presents results for high priced and low priced restaurants respectively. We could still observe positive coefficient of MD_t*T_i. However, this coefficient for high priced restaurants is lower than that coefficient for all restaurants which is also lower than the coefficient for low priced restaurants. The results indicate that the effect of system change is not the same across different groups of restaurants. The impact is higher for low priced restaurants and lower for high priced restaurants, thereby support H3.

Table 4. Difference in Difference Analysis

	Model (1) All restaurants	Model (2) High priced restaurants	Model (3) Low priced restaurants
	Rating	*Rating*	*Rating*
$\boldsymbol{T_i}$	0.069***(0.028)	0.016 (0.031)	0.248***(0.053)
$\boldsymbol{MD_t}$*$\boldsymbol{T_i}$	0.154***(0.030)	0.149***(0.035)	0.168*** (0.060)
$\boldsymbol{logn_r}$	-0.047***(0.011)	-0.059*** (0.013)	-0.020 (0.018)
Restaurant Fixed Effects	Yes	Yes	Yes

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

6.3 Deviation

The results on deviation are presented in Table 5. We use all data after January 2009 when *TripAdvisor* changed its rating system. Column (1) to (2) use data of *Yelp* and *TripAdvisor* separately. Column (3) use the combined data of *Yelp* and *TripAdvisor*. We also add restaurant fixed effects that would control for any unobserved restaurant effects. The coefficients are significantly positive for *Yelp* and negative for *TripAdvisor*.

The results suggest that with the increase of the number of ratings, the absolute difference between previous average rating and the next rating increase in single-dimensional rating system but decrease in multi-dimensional rating system. Column (3) shows that the difference between single-dimensional rating system and multi-dimensional rating system is significant. That is, 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. H2 is supported.

Table 5. Deviation Effects Estimation (DV=Difference from Mean Rating)			
	(1) *Yelp*	(2) *TripAdvisor*	(3) *Yelp and TripAdvisor*
Sequence	0.00014***	-0.00031***	0.000078***
T_i	-	-	-0.025***
*Sequence**T_i	-	-	-0.00018***
Restaurant Fixed Effects	Yes	Yes	Yes

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

6.4. Dimension Effect

Figure 4 presents the average overall rating of *Yelp* (second bar) and *TripAdvisor (third bar)* using all data after 2009 when *TripAdvisor* changed its rating system. It also presents the average highest (fourth bar) and average lowest (first bar) ratings of the four dimensions for each restaurant on *TripAdvisor*. It is evident from the figure that the overall rating of *TripAdvisor* (the third bar) lies between the lowest (the first bar) and highest ratings of different dimensions (the fourth bar), while the overall rating *Yelp* (the second bar) closely matches the lowest dimension rating at *TripAdvisor*.

Figure 4 also shows the 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 the average rating of *Yelp*. Although the mean is significantly different, we could observe that these two boxes overlap to a great extent and the distributions are quite similar to each other. Besides, they are not overlapping with the last two boxes which present the distribution of the highest dimension rating of *TripAdvisor* and the 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 feelings. 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. H4a and H4b are supported.

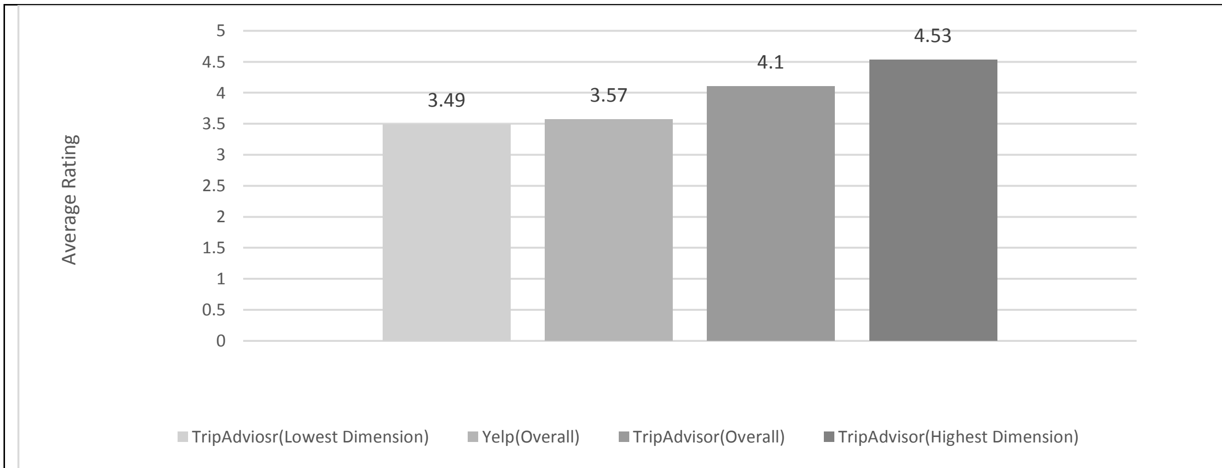

Figure 4. Average Rating Distribution

7. Robustness Checks

7.1. DDD model: Effect of dimensional ratings

As we mention, consumers are not forced to provide dimensional ratings on *TripAdvisor.* Thus, we could observe that the number of total dimensional ratings on *TripAdvisor* is not equal to that of total overall ratings. There is reason to believe that more multi-dimensional reviews would provide more confirmation of quality information and further reduce the uncertainty related to consumption experience, making information transfer easier.

We now extend the presented model (in Equation [9]) to test whether the effect is stronger for those restaurants that have more dimensional ratings. Let n_d denotes the number of existing dimensional ratings on *TripAdvisor* at time t, $logn_d$ is the log transformation of n_d. We use the following formulation:

$$[14] Rating_{ikt} = \beta_1 + \beta_2 * T_i + \beta_3 * MD_t * T_i * logn_d + \beta_4 * logn_r + \alpha_i + \epsilon_{ikt}$$

Here β_3 measures the effects of each additional multi-dimensional rating on the overall rating. The results are shown in table 6.

Table 6. Difference in Difference in Difference Analysis

	Model (1) All restaurants	Model (2) High priced restaurants	Model (3) Low priced restaurants
	Rating	*Rating*	*Rating*
$\boldsymbol{T_i}$	0.084***(0.026)	0.024 (0.029)	0.264***(0.048)
$\boldsymbol{MD_t * T_i * logn_d}$	0.035***(0.011)	0.055***(0.013)	0.073*** (0.021)
$\boldsymbol{logn_r}$	-0.048***(0.011)	-0.061*** (0.013)	-0.021 (0.018)
Restaurant Fixed Effects	Yes	Yes	Yes

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

As expected, the significant positive coefficient of $logn_d$ supports that the effect of system change is dependent on the number of multi-ratings. Contrary to the downward trend in single-dimensional rating system, we could observe an upward trend in multi-dimensional rating system as more ratings are accumulated. This finding is very interesting. Previous literature has shown that downward trending of ratings is widely observed, and the reason is due to self-selection in that consumers who are more enthusiastic about a product would rate it earlier, and such high ratings would "trick" later consumers to try the product but in most cases end with disappointment, therefore, the low ratings. Our findings suggest that multi-dimensional rating system could alleviate this "trick" due to self-selection because multi-dimensional ratings give consumers more reasonable expectation of how much they would like the product and therefore consumers are less likely to be "tricked". Confirmation further strengthen the relationship that multi-dimensional ratings indeed enhance information transfer efficiency. Besides, we could still observe a stronger effect of low priced restaurants than high priced restaurants.

7.2. Deviation Effect

Recall that our primary analyses reveal that ratings are converging in the multi-dimensional rating system but not in the single-dimensional rating system. As a robustness test, we replicate the deviation analysis on *OpenTable* data, which also implements a multi-dimensional rating system but covers a shorter time span of reviews. We report the result of *OpenTable* on deviation effect in Table 7. As is evident in the table, consistent with the finding with *TripAdvisor*, *OpenTable* data also exhibits a convergent trend of multi-dimensional ratings, given the coefficient is negative.

Table 7. Deviation Effects Estimation (DV=Difference from Mean Rating)

	(1) *Yelp*	(2) *TripAdvisor*	(3) *OpenTable*
Sequence	0.00014***	-0.00031***	-0.00020***
Restaurant Fixed Effects	Yes	Yes	Yes

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

Combining results from both Table 6 and Table 7, we could conclude the trend for ratings of multi-dimensional rating system as follows: increasing trend with decreasing marginal effect (i.e. concave function) and finally convergent. Contrasting this finding to previous research (Godes and Silva 2012, Moe and Trusov 2011) which find downward trend of single-dimensional ratings, our research suggests that inefficient information transfer is one major reason that causes the downward trend in single dimensional rating system.

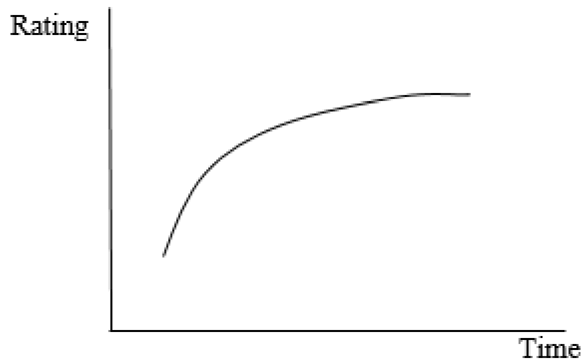

Figure 5. Multi-dimensional rating trend

8. Discussion

8.1. Key findings

This study seeks to extend limited understanding of the information transfer efficiency of different online rating system designs. The results of this study, based on data from two leading online review platforms, first show that consumers are overall more satisfied, therefore higher ratings, with their consumption because they are more able to form realistic expectation from multi-dimensional rating system that is more likely to be confirmed after the adoption of a multi-dimensional system. This finding provides evidence that multi-dimensional rating systems enable more efficient information transfer therefore consumers could form more reasonable expectations and make more informed decisions based on the information from a multi-dimensional rating system (as opposed to single dimensional rating system).

Second, the results of this study indicate that restaurants with lower price level benefit more from adopting a multi-dimensional rating system. This again is consistent with the view that multi-dimensional ratings facilitates information transfer because consumers in general face higher quality and fit uncertainty for low-priced restaurants.

Third, another interesting finding emerged from our research is that when consumers are only allowed to report one single rating (in a single dimensional rating system), they tend to report the rating based on the "least" satisfied aspect in their consumption experience. On the other hand, when they can report separate ratings on different dimensions, then they will be more objective and the overall rating is more likely to reflect average overall experiences on all dimensions.

In sum, our findings suggest that there are benefits of switching from a single-dimensional rating system to a multi-dimensional rating system, especially for experience goods where product attributes are difficult to observe before consumption. Information is transferred among consumers more effectively and consumers are more likely to form rational expectations given multi-dimensional ratings.

8.2. Theoretical Implications

Although previous research have investigated effects of different product attributes on pricing power, hotel ranking and review helpfulness (Archak et al. 2011, Decker and Trusov 2010, Ghose et al.2009, Ghose and Ipeirotis 2011, Ghose et al. 2012), to our understand, there is no research directly compare single-dimensional and multi-dimensional rating system. This study directly addresses whether multi-dimensional ratings facilitate information transfer efficiency and whether multi-dimensional ratings provide net benefits for consumers. We extend limited understanding of the importance of different designs of online rating systems called for by many IS scholars (Archak et al. 2011, Ghose and Ipeirotis 2011). 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. We revisit prior work on the dynamic effects of ratings where a downward trend of single-dimensional ratings is observed (Li and Hitt 2008, Godes and Silva 2012, Moe and Schweidel 2012). We show that such bias may be reduced 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. This study also extends extant research on how IT-enabled technologies could reduce consumer product uncertainty (Dimoka et al. 2012, Kwark et al. 2014).

8.3. 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. For products or services with higher inherent quality and fit uncertainty, it is suggested that a multi-dimensional rating system be adopted. 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. Besides, our results suggest low price restaurants would benefit more from a multi-dimensional rating system than high price restaurant in terms of transferring information to consumers. Therefore, it is particularly important for low price restaurants to encourage (or even incentivize) their customers to provide multi-dimensional ratings.

8.4. Limitation and Future research

As with most observational studies, this study is not free of limitations. First, 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 be generalized to other types of products where consumers may observe product attributes easily. 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 and 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. Note that in this study, we focus on information transfer efficiency which 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. Third, it is possible that additional information could be obtained from text reviews (Pavlou and Dimoka 2006) or extracting different product attributes from review the 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 the different dimensions of the restaurant through average dimension ratings displayed on the restaurant home page. However, it may take several times longer to obtain information on a single-dimensional rating system by reading the text reviews.

8.5. Conclusion

Based on a quasi-experimental difference-in-difference framework, our study utilizes a novel data set combining data from two 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 informed purchasing decisions and happier customers. This effect is more effective for low-priced restaurants. Consumers tend to report ratings to express their strong negative feelings in single-dimensional system and average experience in multi-dimension system. Ratings follow upward and convergent trend 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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