A Cross-Category Analysis of the Effects of Consumer Reviews and Ratings

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A Cross-Category Analysis of the Effects of Consumer Reviews and Ratings

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ABSTRACT

Online consumer ratings and reviews have become very popular among online retailers and are found to influence the sales of experience goods. However, their effects on the sales of search or quasi-experience goods remain unknown. Using data collected from Amazon.com, we examine how the impacts of consumer ratings and reviews differ across product categories. Our results suggest that the sales of experience goods such as books are affected by consumer ratings and reviews, but the sales of quasi-experience and search goods such as digital cameras and USB flash drives are not. In addition, as the price of an experience item increases, consumer ratings and reviews become more influential on sales.

KEYWORDS

Word of mouth, search good, experience good, electronic commerce, Amazon.com.

INTRODUCTION

Online retail sales have experienced tremendous growth since online retailers first emerged in the mid 1990’s. Many retail websites today allow consumers to post product ratings and reviews. According to Walsh (2005), the use of consumer reviews and ratings at Amazon.com, together with its detailed product descriptions and reviews written by in-house staff, allowed Amazon.com to create unique contents that attract Internet traffic, affect consumer purchase decisions, and build trust. Hence, it is not surprising that more than 40% of online retail websites offer consumer ratings and reviews (Gogoi, 2007).

Given retailers’ wide use of consumer ratings and reviews, many researchers have examined the impact of this special kind of online word of mouth on consumer behavior and retailer revenues and profits (e.g., Chen and Xie, 2004; Dellarocas, Awad and Zhang, 2004; Duan, Gu and Whinston, 2005). However, the products examined are limited to categories such as books, movies, and wine, and results so far have been inconclusive. This paper contributes to the extant literature by examining how the impact of consumer ratings and reviews on consumer behavior and retailer revenues may differ across product categories. We categorize products into search, quasi-experience, and experience goods based on the degree to which consumers can learn about product features and quality prior to purchase (Choi, Choi and Lee, 2006; Girard, Korgaonkar and Silverblatt, 2004). For example, features and qualities of search goods such as blank media and USB flash drives can be easily specified and communicated to consumers prior to purchase through their capacity and supported data write or transmission speed. In contrast, experience goods such as books contain mainly non-quantifiable features and their qualities cannot be directly communicated to consumers before the purchase and consumers have to actually use the products in order to learn about its quality. In between search and experience products, we have quasi-experience products such as digital cameras that have some product attributes such as the total pixel count and optimal zoom that can be specified but others such as image quality and ease of use that cannot.

Using consumer ratings and sales data collected from Amazon.com, we show that consumer ratings affect the sales of experience goods but not as much for the sales of search goods, suggesting that consumers pay more attention to others’ ratings and reviews when they cannot directly infer product features and qualities from product descriptions. Moreover, the impact of consumer ratings and reviews on sales strengthens as the price of an experience good increases, pointing out the importance of consumer ratings and reviews to higher-priced experience goods.
The remainder of this paper is organized as follows. We review related literature on online word of mouth and on search vs. experience goods and develop our hypotheses in the next section. After that, we present our samples, followed by a discussion on our econometric model. We next present the results and conclude with a discussion on the implications of our findings.

**LITERATURE REVIEW AND HYPOTHESES**

In this section, we first review theoretical and empirical research on online consumer ratings and reviews. Next, we discuss the marketing literature on search and experience products.

**Theoretical and Empirical Research on Online Word of Mouth**

Theoretical research on online word of mouth examines the impact of online consumer ratings and reviews on firm strategies and profits, consumer surplus, and social welfare. Chen and Xie (2004) consider online consumer reviews as one component of a firm’s overall marketing communications mix and examine conditions under which the online seller may benefit or hurt from the availability of consumer reviews. Chen and Xie (2005) analyze how firms react to third-party product reviews (e.g., from magazines such as PC Magazine and Consumer Report or websites such as CNET.com). Jiang and Chen (2007) analyze the effects of online reviews and ratings on vendors’ profitability, consumer surplus. Research also suggests that firms may manipulate online consumer reviews willingly by disguising as consumers and promoting inferior products (Mayzlin, 2006) or reluctantly (and strategically) to prevent or reduce biased consumer perceptions due to other firms’ manipulative behavior (Dellarocas, 2006).

Empirical research on online word of mouth has mainly focused on experience goods such as books, movies, DVDs, videos, wine, and new television shows, and the results are mixed. Some researchers found evidence that consumer ratings and reviews affected book sales (Chevalier and Mayzlin, 2006), the sales growth in the craft beer industry (Clemons, Gao and Hitt, 2006), and the total revenue of a movie (Dellarocas et al., 2004). In contrast, Duan et al. (2005) found the number of online user ratings of a movie but not the average of the ratings affected its box office revenues. Similarly, Davis and Khazanchi (2007) found that introducing online customer reviews led to increased sales but higher average consumer ratings did not affect sales. Chen et al. (2006) investigated the quality differences of consumer reviews and showed that reviews voted as being more helpful were more influential in affecting consumer book purchase decisions. In addition, the sales of less popular books were affected more by such reviews.

However, there is also evidence that online product ratings and reviews might not be indicative of the true product quality (Hu, Pavlou and Zhang, 2006), which relates to the self-selection bias Li and Hitt (2004) observed on the decline of average product ratings on Amazon.com, as consumers who post reviews for a product might have different tastes compared with the general consumer population.

Our review of previous research on the online word of mouth suggests that most focuses on experience goods and the empirical results are mixed. In this research, we expand to search products and compare the impacts of online consumer ratings and reviews across product categories.

**Search versus Experience Goods**

Research examining information asymmetry in the offline channels has categorized products and services as search, experience, or credence goods or services based on the ease of obtaining product information (Darby and Karni, 1973; Klein, 1998; Nelson, 1970; Nelson, 1974). Search products have dominant attributes that can be sampled and evaluated prior to purchase; examples are clothing and furniture. In contrast, the product attributes of experiences goods such as vacations and entertainment shows can be evaluated only after the purchase and consumption experience. For credence goods such as legal services and education, consumers who do not have the professional knowledge may not even be able to evaluate the products or services after the consumption.

The digital channel enables online retailers to present product information using a combination of text, graphics, audio and video. Even though it is possible to sample products such as CDs online prior to purchase, the same cannot be said for other products such as clothing and furniture. Hence, some search products in the offline channel have been turned into experience goods in the digital channel. To overcome this inherent disadvantage of the digital channel, online retailers such as Amazon.com allow consumers to post their own images taken using a digital camera on the product’s page, which gives potential buyers additional information about the image quality of the camera.
In addition, de Figueiredo (2000) categorized e-commerce products into four categories including commodity, quasi-commodity, look-and-feel, look-and-feel with variable quality. Commodity products are those whose quality can be easily communicated through product description. Paper clips and nails are examples. For quasi-commodity products, the quality varies across different products but remains pretty much the same for different units or copies of the same product. Books and CDs are examples. Once a specific book is chosen, different copies of the same book being sold by different retailers are commodities. Look-and-feel goods are those whose quality cannot be easily communicated through the Internet. Examples are non-brand name clothes and houses. Finally, examples of look-and-feel goods with variable quality are used cars and fresh produce. The quality of these products will vary from unit to unit even after the search process.

We recognize the similarity between the search vs. experience goods and the commodity vs. look-and-feel products categorizations. In this paper, we use the former categorization and examine how the quantifiability of a product’s attributes moderates the impact of online consumer ratings and reviews on product sales. For search goods, consumers can directly learn about product characteristics and qualities based on product descriptions and specifications. Hence, online ratings and reviews will have a smaller impact on consumers’ purchase decisions and product sales. For experience goods, due to the lack of quantifiable product information, consumers rely more on the ratings and reviews to learn about the quality of a product and the degree to which it matches their tastes and preferences. Hence, the ratings and reviews for such products become more important. We do not examine credence goods such as legal services or education as we only focus on Amazon.com and they do not provide such products or services. Hence, we have:

H1: Online consumer ratings and reviews affect the sales of experience and quasi-experience goods more than they affect the sales of search ones.

As the price of a product increases, the purchase becomes more significant to a consumer. As a result, the consumer will be more motivated to conduct a more thorough search and compare alternative products to make the right decision. Under this scenario, the consumer may pay more attention to online ratings and reviews. As a result, we expect:

H2: As the price of an experience or quasi-experience good increases, the impact of consumer ratings and reviews on sales will strengthen.

SAMPLES

We selected three categories of products – general personal finance books, point-and-shoot digital cameras, and USB flash drives – to represent search, quasi-experience, and experience goods, respectively. We chose these three relatively narrow product categories to control for the impact of variations in consumer demands on the sales and to eliminate the influence of other product category-related factors. For products in each category, we collected data on product descriptions, prices, sales ranks, and customer ratings and reviews from Amazon.com in during a two-to-three-day period in either March or April 2007 using an automated data collection agent following the guidelines suggested by Allen et al. (2006). Previous research has established the robustness of the relationship between a product’s sales rank and the actual sales quantity (Brynjolfsson, Hu and Smith, 2003; Chevalier and Goolsbee, 2003), and empirical research has used sales rank as a proxy for the sales volume (Chen et al., 2006; Chevalier and Mayzlin, 2006). In this study, we follow the same approach and examine how consumer ratings and reviews affect the sales ranks of different products. Because Amazon.com calculates its sales ranks based on the combined sales volumes from both new and used products, we also collected data on the number of other offers available and the lowest offer price for each item.

In addition to publishing the consumer ratings and reviews, Amazon.com sometimes select one or two consumer reviews of a product as the spotlight reviews and highlight them in a separate “Spotlight Reviews” section. Consumers can also rate the helpfulness of the reviews on Amazon.com. Chen et al. (2006) have shown the importance of spotlight and most helpful reviews in affecting the sales rank. Hence, in addition to collecting data on the average consumer star ratings, we also collected the average consumer ratings of spotlight reviews and the average ratings of the most helpful reviews when such data were available. For the most helpful reviews, we collected up to ten reviews (based on review availability) that were voted as helpful by the most people and calculated their mean as the average most helpful rating. We report the summary statistics for our three data sets in Table 1. The sales ranks for the general personal finance books, point-and-shoot digital cameras, and USB flash drives were those in books, cameras and photo, and electronics categories, respectively. For digital cameras, we collected data on key quantifiable attributes including the resolution in mega pixels and the optical zoom. For USB flash drives, we collected data on the quantifiable feature of capacity in mega bytes. We included in our sample only products that had at least one consumer rating and that a price was available from a featured seller. We did not consider products that were listed as available only in Amazon.com Marketplace through other “available offers” as their sales ranks might be determined differently compared with the featured products.
Table 1. Sample Descriptive Statistics

<table>
<thead>
<tr>
<th>Product</th>
<th>General Personal Finance Books (N1=1062)</th>
<th>Digital Cameras (N2=431)</th>
<th>USB Drives (N3=192)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>Sales Rank</td>
<td>221166</td>
<td>243969</td>
<td>3103</td>
</tr>
<tr>
<td>Price</td>
<td>16.70</td>
<td>10.19</td>
<td>251.40</td>
</tr>
<tr>
<td>Ave. Consumer Star Rating</td>
<td>4.23</td>
<td>0.74</td>
<td>3.81</td>
</tr>
<tr>
<td>No. of Ratings</td>
<td>19.94</td>
<td>70.26</td>
<td>27.94</td>
</tr>
<tr>
<td>Ave. Spotlight Star Rating</td>
<td>4.07</td>
<td>1.11</td>
<td>4.33</td>
</tr>
<tr>
<td>Ave. Most Helpful Star Rating</td>
<td>4.19</td>
<td>0.81</td>
<td>3.86</td>
</tr>
<tr>
<td>No. Available Offers</td>
<td>57.24</td>
<td>35.93</td>
<td>12.77</td>
</tr>
<tr>
<td>Lowest Available Offer Price</td>
<td>9.28</td>
<td>9.21</td>
<td>178.78</td>
</tr>
<tr>
<td>Pet. Saving Off List Price</td>
<td>26.82</td>
<td>9.20</td>
<td>20.40</td>
</tr>
</tbody>
</table>

Note: The actual numbers of observations used to calculate the statistics for the average spotlight reviews and average most helpful reviews were smaller than the respective sample sizes because not all products had spotlight reviews or consumer voting on the reviews.

ECONOMETRIC MODEL

We perform separate econometric parameter estimations for each of our three data sets. The dependent variable in each model for Product i is –ln(SalesRanki), which is positively related to the sales quantity (unit sales). Similar to Chevalier and Mayzlin (2006), we specify our generic estimation model as:

\[-\ln(SalesRank_i) = v_i + M \ln(P_i^F) + X_i' + N S_i + O_i' + A_i' + E_i' + \epsilon_i\]

where \(v_i\) is a fixed effect that captures the impact of either the first author of a book or manufacturer of a digital camera or USB drive; \(P_i^F\) is the price of the product from the featured seller; \(X\) is a vector of consumer review and rating related variables; \(S\) is a dummy variable indicating whether the product is in stock; \(O\) is a vector of two variables including the number of other available offers and the lowest price of such offers; \(A\) is a vector of product attributes when applicable; \(E\) is a vector of additional variables including a dummy variable indicating whether Amazon.com was the seller of the featured product and a dummy variable indicating the availability of promotional offers for a product. \(\alpha, \beta, \gamma, \Lambda, \Phi, \text{ and } \Omega\) capture the impacts of the aforementioned variables on the dependent variable \(-\ln(SalesRank)\).

RESULTS

We summarize the results for our book data set in Table 2. We have seven models that we number A1 through A7. The common variables to all models are \(\ln(\text{Price})\), \(\ln(\text{Stock})\), \(\ln(\text{DaysSinceRelease})\), \(\ln(\text{NoOtherOffers})\), and \(\ln(\text{LowestOtherOfferPrice})\), as well as the fixed effect of the first author. Because the three rating-related variables—average star rating, average rating of spotlight reviews, and average rating of the most helpful reviews—were highly correlated with correlation coefficients above .7, we entered them one at a time into our estimation models A2 through A7 to avoid multicollinearity problems. We also included the interaction terms between the ratings and \(\ln(\text{Price})\) in Models A3, A5, and A7 to examine how the impact of consumer reviews and ratings may change as the product price changes.

Overall, our results are consistent across the models. When consumer reviews and ratings related variables were added into the model, the R-square increased from .89 in Model A1 to .92 and .94 in Models A3 through A7. This reveals the explanatory power of the rating and review variables.\(^1\) When each of our three average rating variables was added into our estimation model without its corresponding interaction term with \(\ln(\text{Price})\), the parameter estimate was significant and positive. This supports H1 and indicates that higher average consumer ratings lead to increased book sales, which is consistent with empirical findings from previous research (Chen et al., 2006; Chevalier and Mayzlin, 2006). When we added

\(^1\) Please note the R-squares are generally high because of the high number of different first authors for our sample of books.
the interaction terms with $\ln(Price)$, the average star rating remains significant, but the sign reversed. The positive impact of consumer ratings on sales was captured by the interaction term, whose sign was positive. This result provides partial support for H2 and suggests that not only consumer ratings affect book sales but also their impact amplifies as the price of a book increases. In addition, similar to the results Chevalier and Mayzlin (2006) obtained, a larger number of customer reviews on a book was also related to more sales, possibly due to the fact that the variable is indicative of the popularity of the item.

<table>
<thead>
<tr>
<th></th>
<th>A1</th>
<th>A2</th>
<th>A3</th>
<th>A4</th>
<th>A5</th>
<th>A6</th>
<th>A7</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln(Price)$</td>
<td>.201</td>
<td>-.059</td>
<td>3.526</td>
<td>-.194</td>
<td>-.598</td>
<td>.060</td>
<td>1.224</td>
</tr>
<tr>
<td>InStock</td>
<td>.490</td>
<td>-.037</td>
<td>.060</td>
<td>-.1222*</td>
<td>-.1240*</td>
<td>.025</td>
<td>.052</td>
</tr>
<tr>
<td>PctSaving</td>
<td>.074***</td>
<td>.037***</td>
<td>.037***</td>
<td>.042*</td>
<td>.042*</td>
<td>.038***</td>
<td>.038***</td>
</tr>
<tr>
<td>$\ln(DaysSinceRelease)$</td>
<td>-.090</td>
<td>-.285***</td>
<td>-.303***</td>
<td>-.411***</td>
<td>-.406***</td>
<td>-.338***</td>
<td>-.346***</td>
</tr>
<tr>
<td>$\ln(NoOtherOffers)$</td>
<td>-.120</td>
<td>-.174</td>
<td>-.175*</td>
<td>.038</td>
<td>-.043</td>
<td>-.128</td>
<td>-.131</td>
</tr>
<tr>
<td>$\ln(LowestOtherOfferPrice)$</td>
<td>.135</td>
<td>.162*</td>
<td>.137</td>
<td>.338**</td>
<td>.342**</td>
<td>.154*</td>
<td>.144</td>
</tr>
<tr>
<td>$\ln(NoofReviews)$</td>
<td>.715***</td>
<td>.784***</td>
<td>.663***</td>
<td>.661***</td>
<td>.720***</td>
<td>.718***</td>
<td></td>
</tr>
<tr>
<td>AveStarRating</td>
<td>.346**</td>
<td>-.1805*</td>
<td>.718*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(Price)\times\text{AveStarRating}$</td>
<td>.190*</td>
<td>-.066</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AveSpotlightRating</td>
<td>.098</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(Price)\times\text{AveSpotlightRating}$</td>
<td>.316**</td>
<td>1.069</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AveMostHelpfulRating</td>
<td>-.283</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln(Price)\times\text{AveMostHelpfulRating}$</td>
<td>.919</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1003</td>
<td>1003</td>
<td>1003</td>
<td>506</td>
<td>506</td>
<td>966</td>
<td>966</td>
</tr>
<tr>
<td>R-square</td>
<td>.89</td>
<td>.92</td>
<td>.92</td>
<td>.94</td>
<td>.94</td>
<td>.92</td>
<td>.92</td>
</tr>
</tbody>
</table>

Note: The intercepts and fixed effects of the first author are omitted from the parameter estimates. However, the R-squares reflect the contributions of the first author.

Table 2. Empirical Results for the Impact of Reviews on Book Sales

The parameter estimates for the other variables are relatively consistent across the models and the signs are in the expected directions. Books with higher discounts off the list prices and are more recent releases had higher sales. Counter intuitively, books with higher lowest prices charged by other sellers had more sales, possibly due to better conditions of these books.

We next report the results of the empirical analyses on the digital camera and USB flash drive data sets in Table 3. For these two product categories, Amazon.com was not always the featured seller. As a result, we added a dummy variable to capture the impact of Amazon.com being the seller on the sales rank. We also added a dummy variable to examine how promotional offers Amazon.com had might affect the sales. For digital cameras, we also included two product attribute-related variables: resolution in mega pixels and optical zoom. For the USB flash drive, we added a variable $\ln(\text{CapacityinMB})$. Due to the space constraint, we do not report the parameter estimates for these variables in Table 3. Resolution was significant in Models B1 through B4 with positive parameter estimates. Optical zoom was only significant in Models B1 and B2 with positive parameter estimates. $\ln(\text{Capacity})$ was not significant in Models C1 through C4. The 57 USB drives used in Model C3 were all in stock, so we removed this variable from the model.

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We also replaced $\ln(\text{Capacity})$ with Price/MB to test if the price/capacity ratio of a USB drive affected the sales rank. This variable was not significant in any of the four models we ran.
## Table 3. Empirical Results for the Impact of Reviews on Digital Camera and USB Flash Drive Sales

<table>
<thead>
<tr>
<th></th>
<th>Digital Cameras</th>
<th>USB Flash Drives</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B1</td>
<td>B2</td>
</tr>
<tr>
<td>ln(Price)</td>
<td>-1.925***</td>
<td>-2.443***</td>
</tr>
<tr>
<td>ln(Price)*AveStarRating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AveStarRating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Price)*AveSpotlightRating</td>
<td></td>
<td>.856</td>
</tr>
<tr>
<td>AveSpotlightRating</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AveRatingOfMostHelpfulReviews</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(Price)*AveRatingOfMostHelpfulReviews</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AmazonasSeller</td>
<td>.624**</td>
<td>.698***</td>
</tr>
<tr>
<td>Promotions</td>
<td>.303</td>
<td>.272</td>
</tr>
<tr>
<td>N</td>
<td>396</td>
<td>396</td>
</tr>
<tr>
<td>R-square</td>
<td>.63</td>
<td>.71</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is \(-\ln(\text{Sales Rank})\). *** \(p<.01\); ** \(p<.05\), * \(p<.10\). Again, we do not report the parameter estimates of the intercept and the effects of variables such as the manufacturer, resolution in MP, optical zoom, and ln(Capacity); however, the R-squares reflect the contributions of these variables.
Overall, the models show that the number of consumer rating and review has good predictive power for the sales of digital cameras. The R-square increased from .63 in Model B1 to above .70 in Models B2 through B4. The three consumer rating variables are not significant in any of the models, indicating that they are not good predictors of the sales of quasi-experience and search goods. Thus, H1 is supported. In addition, the interaction terms between price and the consumer rating variables are not significant. H2 is not supported.

For digital cameras, higher prices would lead to decreased sales. In contrast, in-stock items, newer models, those with more offers and higher prices from other sellers, and those that were sold by Amazon.com enjoyed higher sales.

For USB flash drives, a higher discount off the list price was associated with reduced sales, which is counterintuitive. The reason might be due to the temporal price decline trend for USB flash drives. As technologies improve, USB drives become cheaper and hence the percent of discount off the list prices tends to increase. However, these products may also become obsolete as new ones with higher storage capacities and other features are introduced in the market. In addition, USB drives sold by Amazon.com generally enjoyed more sales than those offered by other sellers.

DISCUSSION AND CONCLUSIONS

In this study, we compare the impacts of consumer ratings and reviews on sales across three product categories—books, digital cameras, and USB flash drives—which represent experience, quasi-experience, and search goods, respectively. Using data collected from Amazon.com, we have the following results.

First, we find that the impacts of consumer ratings and reviews on the sales ranks of these three types of products are indeed different. The sales of experience goods such as books increase as consumer ratings and reviews improve and more consumers post their reviews and ratings. In contrast, the sales of quasi-experience and search goods such as digital cameras and USB flash drives are not affected by consumer ratings or reviews. When consumers can infer product features and qualities from product descriptions, they rely less on other people’s reviews.

Second, for experience goods such as books, the positive impact of consumer ratings and reviews on sales strengthens as the price of an item increases. When the price of a product increases, the purchase becomes more significant to the consumer. Hence, the potential benefits of comparing alternative products to make the right decision will increase.

Third, we identify additional factors that may affect sales. For example, a larger number of additional sellers of a product and a higher minimum price through such sellers increase its sales. These are reasonable results since Amazon.com’s sales ranks are based on both its own and Amazon.com marketplace sales. For books, heavier discount off the list price promotes sales. In contrast, for USB flash drives where the prices tend to decline over time, heavier discount is associated with weaker sales as new products with higher qualities and more features force the obsolete products to be heavily discounted to sell.

Our research provides insights to both academic researchers and business practitioners. First, we expand the product categories examined to search and quasi-experience goods, giving academic researchers a broader understanding of the impact of online consumer ratings and reviews. Second, our findings are helpful to online retailers that are considering adding consumer reviews to their websites. For those primarily selling search goods, such a feature might not justify the costs as consumer reviews have minimal impact on sales. On the other hand, companies selling experience goods should have consumer ratings and reviews systems in place to promote the online word of mouth and attract customers to their sites to buy products and create user contents (reviews and ratings).

Our research has the following four limitations. First, our samples are cross-sectional data collected at one point in time only. We plan to use a difference-in-difference approach (Chen et al., 2006; Chevalier and Mayzlin, 2006) to examine how changes in consumer ratings and reviews affect changes in the sales rank. Second, despite the preliminary support for our hypotheses based on the data collected from Amazon.com, the results could be due to sample size differences and we cannot conclude on the causality. We plan to conduct a laboratory experiment to investigate the impact of consumer ratings on purchase decisions of search, quasi-experience, and experience goods. Third, we did not examine the impact of consumer ratings and reviews on the sales of credence goods as Amazon.com does not offer such products or services. Fourth, we examined only one type of products in each of the search, quasi-experience, and experience good categories. Future research can examine additional products to cross-validate our findings.

ACKNOWLEDGMENTS

We thank the AMCIS track and mini-track chairs and two anonymous reviewers for their feedback. Bin Wang thanks the University of Texas-Pan American Faculty Research Council for partial support.
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