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Abstract

Quality uncertainty and high search costs for identifying relevant information from an ocean of information may prevent customers from making purchases. Recognizing potential negative impacts of this search cost for quality information and relevant information, firms began to invest in creating a virtual community that enables consumers to share their opinions and experiences to reduce quality uncertainty, and in developing recommendation systems that help customers identify goods in which they might have an interest. However, not much is known regarding the effectiveness of these efforts. In this paper, we empirically investigate the impacts of recommendations and consumer feedbacks on sales based on data gathered from Amazon.com. Our results indicate that more recommendations indeed improve sales at Amazon.com; however, consumer ratings are not found to be related to sales. On the other hand, number of consumer reviews is positively associated with sales. We also find that recommendations work better for less-popular books than for more-popular books. This is consistent with the search cost argument: a consumer's search cost for less-popular books may be higher, and thus they may rely more on recommendations to locate a product of interest.

Keywords: Recommendation system, feedback mechanism, virtual community, digital word-of-mouth, search costs

Introduction

Without doubt, one of the most important impacts of widespread use of the Internet and other information technologies is that it lowers consumer search costs significantly. Previous literature has noted that the presence of consumer search costs can result in inefficient allocation of resources because consumers may not get what they like; it may also prevent customers from purchasing, leading to an inefficient amount of consumption (Stiglitz 1989). Therefore, the reduction in consumer search costs has important implications on firm strategy and consumer behaviors.

We can broadly distinguish between three types of search costs due to imperfect information (Stiglitz 1989). The most commonly studied search costs are search costs for product information, in particular, prices and locations of stores. When there is imperfect information about prices charged at different stores or when consumers do not know where the (next) seller is located, or when it is too costly to get to the next store, it may result in inefficient consumer search or purchase. In addition to search costs for prices and stores, there are also search costs for quality information, especially for experience goods. Experience goods are goods in which quality is only known to customers when they have actually experienced them. That is, consumers can not easily deduce the quality solely from their product or service descriptions. Finally, consumers may also experience search costs (or processing costs) to identify a product that fits them when products are imperfect substitutes.

Most previous literature on online markets have focused on the search costs for prices and stores and looked at how the availability of search and shopping engines reduces consumer search costs and impacts consumer behaviors (Bakos 1997; Brynjolfsson and Smith 2000). However, the reductions in search costs for prices and stores accentuate search costs for quality information and search costs for fit. Indeed, online transactions typically occur between entities that have never met, thus participants, either seller or buyer, are especially vulnerable to opportunistic behaviors (Ba and Pavlou 2002). Quality uncertainty for products can also be higher for online buyers, relative to buyers in traditional business settings where people may learn about product quality by "kicking the tires." In addition, search costs for fit are also higher in online markets. As noted by Stiglitz (1989), in the absence of information, products may be viewed as perfect substitutes, but as information becomes available, they may become imperfect substitutes, giving rise to search costs (or processing costs) for fit. On the other hand, one can easily get a much larger set of alternatives in online markets compared to what one can get in offline markets, which again raises consumer search costs for finding the *ideal* product. Recognizing that the existence of search costs for quality information and search costs for fit can continue to hold consumers back, even though consumer search costs for prices and stores are eliminated, firms have adopted a number of strategies hoping to reduce these two sources of search costs.

One such effort is the development of online feedback mechanisms or virtual communities. An important capability of the Internet is its bi-directionality, allowing consumers to share their opinions and experiences easily with each other in a large scale, as opposed to word-of-mouth from acquaintances in traditional markets (Dellarocas 2003). This digitized word-of-mouth has the potential to reduce the quality uncertainty associated with a purchase and may become an important source of information for consumers.

Previous literature on online feedback mechanisms has mainly focused on the *quality* information (or uncertainty) associated with the participants (usually sellers) of a transaction in online markets, especially online auction markets, such as eBay.com (Ba and Pavlou 2002; Houser and Wooders 2000; Lee et al. 2000; Lucking-Reiley et al. 2000; Resnick, et al. 2002). The main questions studied are how online feedback mechanisms may help build trust between different parties in the online markets, and how positive or negative ratings on sellers impact the final prices, number of bids received as well as the probability of a sale. For example, Schubert and Ginsburg (2000) and Ba (2001) discussed how virtual communities can build trust among members and foster confidence in consumers' purchasing decisions. Ba and Pavlou (2002) found that online feedback mechanisms can induce trust, which in turn can mitigate information asymmetry and as a result generate a price premium for goods sellers. Pavlou and Gefen (2004) studied how institution-based trust based on online feedback mechanisms, third-party escrow services, and credit card guarantees may induce trust or reduce consumer-perceived transaction risks with the sellers.

In contrast with prior literature on online feedback mechanisms, which has mainly focused on the quality information associated with the participants of a transaction, our focus is on the product itself. In reality, it is perhaps more common for consumers to exchange information and opinions on products, especially for experience goods, than they do on sellers. By knowing other consumers' experiences with a particular product, the quality uncertainty associated with this particular good can be reduced, which, in turn, can have an impact on consumers' decision making. On the other hand, to the extent that consumer ratings may be manipulated by some strategic stakeholders or interest groups, this information may be discounted by potential buyers. We are interested in understanding whether online feedback mechanisms indeed reduce quality uncertainty and the impact of the quality information concerning a product on consumer demand.

Firms have also invested in technologies, such as recommendation systems and customer profiling techniques, to reduce consumer search costs for fit by helping them identify their ideal product and reducing possible "misfit costs" by presenting products they are more inclined to like. For example, Amazon.com, among others, has been using a recommendation system for a few years. Working on the principle of collaborative filtering, Amazon.com provides a short list of recommendations on books or CDs to customers, based on a wealth of information gathered from other customers. These recommendations have the potential of reducing consumer search costs because consumers may not have to look at a broad range of alternatives before they know what might fit them. Previous literature has recognized the important of recommendation systems as a way to exploit valuable consumer information acquired, and as an important personalization tool in online marketplaces (Schubert and Ginsburg 2000; Van de Kar, et. al. 2004); however, to our knowledge, there is no research that has empirically looked at the *value* of recommendations. Our interest is to investigate whether recommendations indeed lead to lower search costs for fit.

In sum, the goal of this research is to investigate the effectiveness of technology investments on virtual communities and recommendation systems—specifically, to study the impact of recommendations and consumer feedback on consumer demand. A relevant study by Chevalier and Mayzlin (2003) examines the effect of consumer reviews on relative sales of books on Amazon.com and BarnesandNoble.com. However, they do not consider the effect of retailer recommendations, which can potentially have some impact on consumer demand as well. As a result, they may not be able to infer any relationship between differences in consumer reviews and difference in sales because the systematic differences can also be caused by retailer recommendations. We consider both consumer feedback and retailer recommendations in our study, allowing us to distinguish between the two effects.

Understanding the impact of online recommendations and consumer feedback has important implications on retailer strategies and the dynamics of the market. If consumer feedback is found to be a significant driver of sales, then authors, publishers, and retailers may want to devote more efforts to managing consumer feedback, and can derive valuable information for the development and marketing of new products, which may otherwise only be obtainable through expensive customer interviews. In addition, understanding the effectiveness of recommendation systems can help shape the future technology strategies of firms. The effectiveness of recommendation systems may depend on the level of consumer search costs. Recommendations are only needed when consumer search costs are high. If consumer search costs are low (i.e., they can easily identify a product that fits them), then firms may not find it worthwhile to invest in recommendation systems or similar technologies.

We gather data from Amazon.com, one of the pioneers in the use of information technology, to study the impact of online feedback mechanisms and recommendation systems on consumer demand at the Web site. Our results indicate that more recommendations indeed improve sales at Amazon.com; however, consumer ratings are not found to be related to sales. On the other hand, number of consumer reviews is positively associated with sales. We also find that recommendations work especially well for less-popular books, such as technical books. This is consistent with the search-costs argument. Consumer search costs for less-popular books may be higher, thus, they may rely on recommendations to locate a product of interest.

The rest of the paper is organized as follows. In the next section, we present our hypotheses. Data and the model are described in the third section. The empirical results are shown, followed by the discussions and conclusions.

Hypotheses

We are interested in understanding the effectiveness of consumer feedback and online recommendations—specifically, whether the availability of consumer feedback and retailer recommendations reduces consumer search costs. We try to get some insights to this research question in the context of booking selling at Amazon.com. Amazon.com is considered to be "increasingly significant as a measure of what's important out there" with its advance use of information technology, and readers and publishers are increasingly relying on Amazon.com as an information source for their purchasing or publishing decisions (Schubert and Ginsburg 2000).

Does Consumer Feedback Lead to Reduced Search Costs for Quality Information?

If consumer feedback indeed reduces search costs for quality information, then we should observe that consumer feedback has an impact on sales. Therefore, while consumer search costs for quality information may not be directly measured, we may obtain some insight by investigating how consumer feedback affects sales.

Consumer Ratings vs. Sales

People often refer to others' opinions or experiences before spending on some products, the quality of which they are uncertain. The feedback from other users can serve as a quality index for a product of interest and thus can potentially reduce the quality uncertainty faced by a potential customer, and can confer a higher degree of confidence to the customer's purchasing decision (Schubert and Ginsburg 2000). As a result, there is some reason to believe that the availability of consumer feedback may reduce quality uncertainty. When quality uncertainty is reduced, we would observe that consumers are more likely to purchase books with higher ratings than those with lower ratings, other things being equal.

On the other hand, as noted by Pavlou and Gefen (2004), feedback mechanisms are likely to be effective only if the participants perceive that the feedback provided is an accurate and credible depiction of the marketplace and other buyers' experiences. Thus, if consumers do not find the ratings trustworthy or meaningful, they will not take these ratings into account in their decision making. For example, many previous studies on online feedback systems have found that most of the ratings are relatively positive (Godes and Mayzlin 2003; Resnick and Zeckhouser 2002), and when there is only little variance across books, consumers may not find these ratings informative and thus do not factor this into their decision making. Many other factors may also lead to a situation where consumers do not "believe" so much in the ratings, for example, when there is high variance in the readers' opinions on the same book, or when the ratings represent only a small number of readers' opinions. Moreover, to the extent that consumers understand that strategic behaviors may occur, for example, authors and publishers may have high incentives to post favorite reviews for their book titles, these reviews may be discounted by potential buyers (Chevalier and Mayzlin 2003).

In addition, since books are essentially differentiated goods and consumer tastes could be very different, a consumer may get a book regardless of how other customers like or dislike the book, as long as she thinks she will like it. As a result, reviews may not have any prominent effect on book sales. In addition, the rating of a certain book can only have an impact when consumers are actually aware of this book. If a consumer doesn't know about or browse a particular book, then the rating of this book remains unknown to this customer, and thus it will have no impact on consumer decision making.

Therefore, we do not posit any specific hypothesis regarding consumer reviews and sales. However, following the conventions of empirical research, we give the following hypothesis for the purpose of hypothesis testing:

> ***H1: Higher consumer ratings are positively associated with higher sales.***

Numbers of Reviews vs. Sales

A high number of reviews may indirectly indicate the momentum of the book in the market since people are usually more interested in chatting or exchanging opinions on things that are "hot" or popular. More enthusiastic discussions may trigger consumer interests and drive more sales, thus we expect that higher numbers of reviews are associated with higher sales, after accounting for other factors. However, since one may also argue that higher number of reviews is a direct result of higher sales, we do not attempt to imply any causality between higher number of reviews and higher sales, but that there is a positive relationship between the number of reviews and sales.

> ***H2: Higher numbers of reviews are positively associated with higher sales.***

Number of reviews can also have an impact on consumer search costs. A higher number of reviews may represent objectivity, and consumers may be more willing to trust the reviews when they represent a larger audience. Therefore, it may be reasonable to believe that consumers may put more weight on consumer ratings when the ratings are high and the numbers of reviews are large. Thus, we expect

> ***H3: Higher ratings together with higher number of reviews are positively associated with higher sales.***

Do Recommendations Lead to Reduced Search Costs for Fit?

One prominent property of the Internet is that information abounds. Contrary to traditional markets where buyers usually need to make a decision without knowing all the relevant information because information is difficult to obtain (i.e., search cost for information is high), such constraint does not exist in online markets. For example, traditionally, when a buyer is interested in buying a book on, say, investing, her choice set is usually limited to the book titles a physical bookstore carries. However, in online markets, one can easily put in a keyword and identify a much larger set of related books, and may thus get a book that fits her better. This low search costs for information distinguishes the Internet from other channels. However, as stated perfectly by Herbert Simon, "a wealth of information creates a poverty of attention." The scarce resource in this information-rich context (e.g., the electronic markets) is attention; the large amount of information creates processing problems for individuals, which creates another source of search costs—search costs for fit.

Recommendation systems are used by firms with the hope of reducing consumer processing costs by helping customers in narrowing their choice set. Suppose recommendations reduce consumer search costs for fit, then we should observe that recommendations are positively related to sales. Intuitively, it seems reasonable to believe that more recommendations would lead to higher sales, since "the more roads lead to a city, the more often this city is bound to be visited."[1] However, that the city is more likely to be visited is true only when consumers are just random walking (i.e., they do not have a clear idea about where to visit), but if consumers know which city to visit and how to get there, then it may not matter where other roads lead. Similarly, we expect that recommendation systems work only if consumers face high search costs for identifying a product they would like and recommendations indeed reflect the needs of the customers (i.e., they are taken into account when the consumers make decisions). For example, when consumers have no idea or are uncertain about which book, within a certain domain, to get, they may find it very helpful to use the recommendations from retailers to form their choice set. In this case, we would expect more recommendations to be positively associated with sales.

On the other hand, consumers may not consider retailer recommendations when the recommendations do not reflect their needs, or when their search costs and information processing costs are small (i.e., consumers know exactly what they want). For example, the search costs for bestseller books can be low since customer awareness for these books can be very high, thus consumers' purchase decisions may not be affected by these recommendations. Thus, we have the following hypotheses:

> ***H4: More recommendations are positively associated with higher sales.***

> ***H5: More recommendations are not associated with higher sales for more popular books.***

Data and Model

The Data

We developed a data acquisition program with Python 2.3.2, a Web agent programming language, to gather data from the Amazon.com Web site. We extract relevant information from the Web page on each book in the sample, including ISBN, title, actual price, savings (i.e., the difference between list price and actual price paid), publisher, published date, number of customer reviews for each book, average customer rating for each book (in a five-star scale),[2] book subjects, as well as sales rank. A lower sales rank corresponds to higher sales volume.

We also derive the number of recommendations each book has received. Amazon.com provides a recommendation book list prefaced with "Customers who bought this book also bought" for each book, with collaborative filtering as the underlying principle. The number of recommendations was counted based on the information contained in "Customers who bought this book also bought"; that is, if another book had the book of interest as an item on the recommended list of "Customers who bought this book also bought," then the recommendation number of the book of interest was increased by one.[3]

The data was gathered in December 2003. We distinguished three groups of books: bestsellers, popular books, and less-popular books. The bestseller group included the 100 bestselling books Amazon provided. A total of 352 books were randomly drawn from the sales ranks between 101 and 9,999, which we defined as the popular books. The less-popular books were from the sales rank over 10,000. A total of 241 titles were randomly generated from this group. Thus, we gathered a total of 693 different book titles. We excluded books that were unavailable directly from Amazon due to out-of-print (although they were available in the secondary market maintained by Amazon), leaving us with 610 different books for our analysis, with 100 from the bestselling list, 348 from the popular group and 162 from the less-popular group.

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[1]We thank an anonymous reviewer for providing this interesting analogy.

[2]When consumer rating is available for a book, it takes on one of the following values: 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, and 5 stars.

[3]The strategy on how we derive the number of recommendations for each book is omitted here due to space constraints, but is available from the authors upon request.

The Model

To study the effects of consumer reviews and recommendations on sales, we fit the following model. The log-transformation is commonly used in models of this sort in the marketing literature.

$$\ln(rank_i) = \beta X_i + \gamma C_i + \lambda R_i + \varepsilon_i$$

Where $rank_i$ is the sales rank of book *i* at Amazon.com, X_i is a set of control variables characterizing book *i*, including price, discount, as well as year of publication, and book category, while β captures the effects of these variables on sales. Specifically, $X_i = [\ln(\text{price}_i), \frac{\text{savings}_i}{\text{list price}_i}, \text{publish year}_i, \text{category}_i]$, with price_i denoting the price actually paid (i.e., list price – savings). In addition, recognizing that not all books have the same level of demand, we also include book subject in the regression to capture possible demand effect for each subject (category_i). We include consumer reviews information in C_i, including average consumer review score as well as the number of reviews for book *i* (i.e., C_i = [ln(review no._i]), with γ capturing the effects of consumer reviews on sales. Number of recommendations book *i* received is summarized in the variable R_i = ln(no. of recommendations_i), and λ indicates the effect of recommendations on sales. Finally, ε_i captures the random error. Our primary interests are γ and λ. Note also that lower ranks indicate higher sales, so a negative estimate implies a positive relationship with sales, while a positive estimate indicates a negative relationship with sales.

Empirical Results

General Characteristics

Summary statistics of the key variables are presented in Table 1. Note the discount of a book is defined by $\frac{\text{savings}_i}{\text{list price}_i}$. The average discount at Amazon.com is 20 percent off, with a mean price of $20 and average savings of $4. Average number of reviews is about 96, but there is a huge variance in the number of reviews across books. Recommendation number, on the other hand, averages 6.

We then look at the extent and content of the consumer feedback as well as the extent of recommendations.

Tables 2 and 3 show the distributions of consumer reviews and ratings. There is high variation in terms of number of reviews received by each book: while about 17 percent of the books receive no reviews, some books can have as many as several thousand reviews. Another interesting observation is that the average consumer ratings of the books are quite high, about 70 percent of the books receive four stars or higher. This finding is consistent with previous findings that most of the feedback is positive. For example, Resnick and Zeckhouser (2002), based on the data extracted from eBay, found that only 0.3 percent of the ratings are negative, while more than 51 percent of the feedback is positive, with no feedback accounted for about 48 percent of the time. Godes and Mayzlin (2003) also showed that 70 percent of the online conversations about TV shows are positive.

Table 1. Descriptive Statistics

Variable	Number of Observations	Mean	Standard Dev	Median
Discount	610	0.20	0.14	0.28
Review no	610	96.01	279.46	17
Price	610	19.92	24.00	13.00
Saving	610	4.28	4.40	4.00
Review grade*	507	4.32	0.59	4.50
Recom no	610	6.18	6.79	4.00

*The summary statistics reported on Review Grade are conditional on books having received at least one review.

Table 2. Distribution of Consumer Reviews

X	Percent (no. of reviews ≤ x)
0	17%
1	23%
2	25%
17	50%
73	75%
240	90%
731	97.5%
1910	99.5%
4607	100%

Table 3. Distribution of Star Ratings

Star Rating	Count	Percentage
1.5	1	0.2%
2	3	0.5%
2.5	2	0.3%
3	18	3%
3.5	56	9%
4	117	19%
4.5	183	30%
5	127	21%
N/A	103	17%
Total	610	1.00000

Table 4. Distribution of Number of Recommendations

X	Percent (no. of recommendations ≤ x)
0	19%
1	34%
4	50%
10	75%
16	90%
23	97.5%
36	100%

Table 5. Correlation Matrix of the Key Variables

	Log Sales Rank	Share of Savings	Log Price	Log Recom No	Log Review No	Review Grade
Log sales rank	1.0000	-0.5215	0.2463	-0.2316	-0.4326	0.1215
Discount	-0.5215	1.0000	0.1320	0.1699	0.1541	-0.1512
Log price	0.2463	0.1320	1.0000	-0.1594	-0.2629	0.0207
Log recom no	-0.2316	0.1699	-0.1594	1.0000	0.0689	0.0939
Log review no	-0.4326	0.1541	-0.2629	0.0689	1.0000	-0.2543
Review grade	0.1215	-0.1512	0.0207	0.0939	-0.2543	1.0000

The distribution of number of recommendations each book has received at Amazon.com is presented in Table 4. In all, 19 percent of the books were never included in the recommendation lists of any other book at Amazon.com, while some books appeared in the recommendation lists of as many as 36 other books. As mentioned earlier, books are usually recommended by other similar book titles. For example, a children's book is more likely to be recommended by another children's book, and an IO textbook is more likely to recommend another relevant textbook, such as a game theory textbook. So while 36 recommendations seems to be extremely small compared to the whole universe of books, their impact on consumer decision making could be great when a consumer tries to decide what book to buy among a small set of similar book titles.

The correlation matrix of the key variables are presented in Table 5. As evident from the table, we do not observe any high correlations that deserve special treatments for our regression analysis.

The Impacts of Consumer Feedback and Retailer Recommendations on Sales

We fit the model, as described earlier, to our data gathered from Amazon.com. We include price, discount, year of publication, and book category as control variables. Note that we categorize books into four broad categories: fiction and fantasy, technical, children's book, and others. The others category serves as the baseline case.[4] The variables of interests are consumer ratings, number of reviews, and number of recommendations. As mentioned earlier, a positive estimate on a variable suggests a negative relationship with sales, since a higher number with rankings is associated with lower sales.

In the first model (Table 6, model 1), we treat consumer ratings as continuous variables having a linear relationship with sales. However, this may not be reasonable, and those books with no reviews are treated as missing values and are excluded in the regression. Thus, we distinguish between different review scores (1, 2, 3, 4, and 5 stars and the case of no review)[5] in model 2 (Table 6, model 2). Overall, the results indicate that children's books are usually associated with higher rankings at Amazon.com while technical books are associated with lower rankings. This reflects the market demand for these books: the market for technical books is smaller than the market for children's book. Also, robust under various models, we find that higher price is negatively associated with sales, and discount (in percentage) increases sales, as one would have expected. In addition, newer books have higher sales than older books.

As for the constructs of interests, when consumer ratings are treated as continuous variables (model 1), the results indicate that books that receive more reviews are positively associated with higher sales, lending support to H2. However, consumer ratings are not observed to be related to sales, which rejects H1. Recommendations, on the other hand, are positively associated with higher sales, so H4 is supported. Since model 1 excluded books receiving no reviews, some valuable information may be missing there.

[4] We also ran regressions with more detailed category types, and the results are pretty much the same.

[5] We convert x.5 stars to x stars.

Table 6. Statistical Analyses

Term	Model 1	Model 2	Model 3
Intercept	63.59*** (22.572)	57.30*** (20.985)	56.84*** (21.049)
Log price	0.83*** (0.174)	0.52*** (0.137)	0.53*** (0.136)
Discount	-8.91*** (0.652)	-7.70*** (0.570)	-7.53*** (0.572)
P Year	-0.03** (0.011)	-0.02** (0.011)	-0.02** (0.011)
Log review no	-0.43*** (0.059)	-0.42*** (0.058)	-0.51*** (0.090)
Log recom no	-0.33*** (0.089)	-0.48*** (0.082)	-0.48*** (0.082)
Book Categories			
Children's book	-0.83*** (0.231)	-1.00*** (0.214)	-0.93*** (0.219)
Fiction and Fantasy	-0.16 (0.158)	-0.17 (0.152)	-0.18 (0.153)
Technical	0.40** (0.188)	0.51*** (0.163)	0.48*** (0.162)
Review grade	-0.10 (0.156)	—	—
Rating [1]	—	-1.10 (1.570)	-0.67 (1.577)
Rating [2]	—	0.62 (0.763)	0.61 (0.763)
Rating [3]	—	-0.27 (0.387)	-0.25 (0.396)
Rating [4]	—	-0.27 (0.358)	-0.40 (0.366)
Rating [5]	—	-0.07 (0.379)	-0.23 (0.384)
Rating [5]*more reviews	—	—	-0.12 (0.172)
Rating [4]*more reviews	—	—	0.10 (0.186)
Rating [3] or below*more reviews	—	—	-0.11 (0.155)
Observations	507	610	610
R^2	49%	64%	65%

Notes: Dependent variable — log rank. Standard errors in parentheses.
$*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

In model 2, we distinguish between different review scores (1, 2, 3, 4, and 5 stars and the case of no review available)[6] and look at their relationships with sales. Note that the baseline case is when a book has no review. Consistent with the findings in model 1, the star ratings do not appear to be related to sales. But recommendations, again, have a significant effect on sales. These results are robust when we use more detailed rating information, i.e. by breaking the ratings to 10 levels, which distinguish 1.5 from 1, 2.5 from 2, 3.5 from 3, and 4.5 from 4 stars and include the baseline case: when a book has no review.

[6]Again, we convert x.5 stars to x stars.

To test hypothesis 3, we distinguish books that receive more reviews (more than the median number of reviews) and books that receive less reviews (less than the median number of reviews) as well as different star ratings (5, 4, and below or equal to 3 stars). Specifically, we are interested in whether a higher star rating together with higher number of reviews is associated with higher sales. As before, books with no reviews serve as the base case. The results are presented in model 3 of Table 6. The findings on all of the key constructs are basically consistent with those from previous models without the interaction effects. Interestingly and surprisingly, none of the interaction terms are significant, thus rejecting H3.

One concern with previous analyses is that we treat each book the same, beyond factors already controlled for in the regression. However, just like producing a music album, some albums are more likely to be a hit and some more likely to be a flop; unfortunately, it is difficult to predict which one is going to be a hit *ex ante*. We expect there may also be similar unknown factors that drive the demand for each book, yet this unknown factor cannot be controlled for or is not known *ex ante*. To control for this possible unknown factor and to see whether the effects will differ systematically with a different level of demand, we distinguish books into three groups: bestsellers (group 1), popular books (group 2), and less-popular books (group 3), according to their sales ranks at Amazon.com. The bestseller group included the 100 bestselling books Amazon provided. Books in group 2 are drawn from the sales ranks between 101 and 9,999, and group 3 from the sales rank over 10,000. With this treatment, we are comparing books that have the same level of popularity in the market. We then run the same set of regressions with these groups.

The results are shown in Table 7. As we can see from the table, discount continues to play an important rolesin driving sales. As the discount increases, sales also increase. Newer books again have a higher sales level. Price continues to be an important factor of sales for group 2 and group 3, with higher prices leading to lower sales. However, price becomes insignificant for group 1, suggesting that price is less an issue for most popular books. As before, number of reviews is positively associated with sales, although it is not significant for group 2. Interestingly, more recommendations are not necessarily related to sales when we break the analyses in groups. In particular, more recommendations are not effective in driving sales for more popular books (defined by group 1 and group 2), supporting H5, although it is found to be significantly associated with sales for group 3. This is consistent with the search cost argument. For books that presumably have higher awareness (those more popular), consumers may have better information on whether the books fit them or not, thus, they may rely less on the recommendations. In addition, by looking at the composition of book categories across groups, we find that group 3 has a higher share of technical books, so this result may suggest that recommendations may be more effective for technical books.

Interestingly, some star ratings begin to show effects. For group 1, a rating of five stars is positively associated with higher sales, while a rating of two stars is negatively related to sales, as one would have expected. However, for group 2, higher ratings have the "wrong" signs. However, we also observe that the model does a poor job in fitting group 2; this may indicate that consumers are less influenced by these external factors commonly believed to influence sales for books at the medium sales level. This result suggests that there may be some systematic differences across books with different popularity level. While bestsellers may largely be driven by the bandwagon effect, books composing group 2 may be books for consumers with very different tastes and having a better idea about what they want, and thus not relying on the external factors to make their decisions. However, further research may be needed to truly understand consumers' decision making.

On the other hand, book categories also have some interesting results. For example, children's books, although more likely to be associated with higher sales under the aggregate model, are less likely to be placed on the top of the bestseller list. On the other hand, technical books, within group 2, are more likely to be associated with higher sales, while fiction and fantasy types of books are associated with higher sales among other less-popular books.

What Books Are More Likely to Be Recommended?

We also investigate what books are more likely to be recommended, and the results are presented in Table 8, where a positive estimate means a positive relationship. The results indicate that books that receive higher star ratings and a higher number of reviews are more likely to be recommended by Amazon. In addition, books that have deeper discounts and lower prices are more likely to be recommended. Interestingly, we also find that technical books are recommended more, while fictions and fantasy types of books are recommended less. This result may also imply that consumers are more likely to rely on the retailer's recommendation for technical books. For fictions and fantasy books, consumers are more likely to have different tastes, and they may also have a better idea about what types of books or which authors they like the best, resulting in fewer recommendations on these types of books.

Table 7. Regression Results by Groups

Term	Group 1	Group 2	Group 3
Intercept	61.60*** (22.620)	-5.50 (11.766)	-14.71 (24.229)
Log price	0.22 (0.214)	0.26* (0.134)	0.34*** (0.098)
Discount	-2.11** (0.824)	-1.23** (0.481)	-1.06* (0.602)
P Year	-0.03** (0.011)	0.01 (0.006)	0.01 (0.012)
Log review no	-0.26*** (0.057)	-0.01 (0.037)	-0.33*** (0.100)
Log recom no	-0.07 (0.092)	0.03 (0.048)	-0.35*** (0.119)
Book Categories			
Children's book	0.37* (0.209)	0.18 (0.125)	—
Fiction and Fantasy	-0.23 (0.171)	-0.09 (0.082)	-0.57*** (0.214)
Technical	-0.08 (0.251)	-0.20** (0.098)	0.17 (0.132)
Rating [1]	—	-0.88 (0.693)	—
Rating [2]	1.27* (0.590)	-0.76 (0.682)	0.54 (0.479)
Rating [3]	-0.21 (0.314)	0.30 (0.215)	-0.26 (0.254)
Rating [4]	-0.36 (0.255)	0.39* (0.200)	-0.29 (0.210)
Rating [5]	-0.59** (0.290)	0.47** (0.217)	-0.10 (0.172)
Observations	100	348	162
R^2	31%	6%	47%

Notes: Dependent variable — log rank. Standard errors in parentheses.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 8. What Books Are More Likely to Be Recommended?

Term	Estimate
Intercept	-4.41 (10.427)
Log price	-0.30*** (0.067)
Discount	1.26*** (0.279)
P Year	0.00 (0.005)
Log review no	0.06** (0.029)
Book Categories	
Children's book	-0.09 (0.106)
Fiction and Fantasy	-0.41*** (0.074)
Technical	0.33*** (0.080)
Rating [1]	-0.82 (0.779)
Rating [2]	-0.84** (0.377)
Rating [3]	0.37* (0.192)
Rating [4]	0.67*** (0.176)
Rating [5]	0.48** (0.187)
Observations	610
R^2	22%

Notes: Dependent variable — log recom no. Standard errors in parentheses.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Discussion and Conclusions

Previous literature has suggested that search costs may discourage customers from purchasing and may also result in inefficient allocation of resources because consumers may not get what they like. Thanks to advances in information technologies, search costs for price and product information are greatly reduced, and previous literature has paid much attention to the impacts of lowered search cost for price and product information. However, consumers may still face quality uncertainty, especially for experience goods, which cannot easily be resolved simply by browsing the product information. So even though the search cost for price and product information has been reduced, the high search cost for quality information may continue to hold consumers back. On the other hand, the low search cost nature of the Internet also quickly results in an ocean of information, and this wealth of information creates new cost for consumers: a search cost (or processing cost) for consumers to locate the relevant information or a product in which they are interested.

Recognizing possible negative impacts on sales due to the concerns of quality uncertainty and high search costs for relevant information, firms began to invest in technologies to reduce consumer search costs for quality information as well as search costs to locate relevant information. Two of the most significant efforts are the creation of virtual communities that enable consumers to share their opinions and experiences, and developing recommendation systems that help customers identify goods that might be of most interest to them, among a potentially large set of alternatives. We investigate the effectiveness of these technology investments (i.e., whether they lead to lower consumer search costs for quality information and for fit) and study the impact of these efforts on sales based on data gathered from Amazon.com.

Our results show that more recommendations are positively associated with sales, and recommendations work particularly well for less-popular books, such as technical books. On the other hand, higher recommendations do not necessarily lead to higher sales for more popular books. This is consistent with the search cost argument. Consumers may be better aware of the popular books (i.e., lower degree of quality uncertainty), and thus they have a better idea about whether or not they will like a particular book. However, consumer search costs for less-popular books may be higher; thus, they may rely on recommendations to locate a product in which they are interested. This result suggests that the effectiveness of the recommendations depends on the amount of search costs (or processing costs) consumers face in identifying a product they like. Suppose search costs or processing costs are essentially zero for consumers, and consumers can identify an ideal product with limited costs; then these recommendations may not be needed. Overall, our results indicate that *it is more efficient and effective to develop recommendation systems on products that have higher consumer search costs.*

Number of reviews a book has is also found to be positively related to sales. Given that people are more likely to exchange opinions on topics that are hot, the number of reviews a book has may capture the momentum of the book in the market. That is, more enthusiastic discussions may drive sales. However, higher number of reviews can also be a direct result of higher sales, so one may not imply any causality with the relationship. But this result suggests that, *when sales data is not available, one may use number of discussions or reviews as a potential proxy or instrument for sales.* This has important implications on future empirical studies because consumer feedback information is usually readily available online (through BBS, or a variety of virtual communities) while true sales and transaction data can be very hard to obtain in online markets.

Interestingly, consumer ratings of the book are not found to be related to sales. There are many possible explanations for this. For one, since books are essentially differentiated goods and consumer tastes could be quite different, they may get a book they like regardless of how much other customers like or dislike the book. In addition, since most of the books receive relatively high ratings, consumers may not find these ratings informative. These ratings may also be discounted by consumers if consumers believe that these ratings may be manipulated by others. In contrast with our findings, Chevalier and Mayzlin (2003) find a positive relationship between average ratings and sales. This can be due to the influence of retailer recommendations, which are not controlled for in their study. However, further work may be needed in order to reconcile the findings.

This research is one of the first studies to investigate the effectiveness of online recommendations and consumer feedback. Our analyses based on data from Amazon.com have obtained some insights on whether investments on online feedback mechanisms and recommendation systems have reduced consumer search costs, and have identified some relationships between recommendations and sales as well as consumer feedback and sales. Future study may extend this research using a broader or deeper level of data, such as detailed customer comments, or opinions of some "anchor" readers. We may also use data from a different context. For example, it will be very interesting to look at goods that are vertically differentiated,[7] since there could be a higher impact on sales due to a reduction of quality uncertainty for vertically differentiated goods. There are also open issues regarding causality; for example, it may be interesting to study whether a higher number of reviews drives more sales or higher sales drive more reviews, or if they reinforce each other.

[7]When people agree on which good is better than which, within the same category, we say these products are vertically differentiated. For example, people generally agree that a Mercedes car is better than a Yugo car.

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