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Abstract: Online retailers are increasingly using information technologies to provide value-added services to customers. Prominent examples of these services are online recommender systems and consumer feedback mechanisms, both of which serve to reduce consumer search costs and uncertainty associated with the purchase of unfamiliar products. The central question we address is how recommender systems affect sales. We take into consideration the interaction among recommendations, sales, and price. We then develop a robust empirical model that incorporates the indirect effect of recommendations on sales through retailer pricing, potential simultaneity between sales and recommendations, and a comprehensive measure of the strength of recommendations. Applying the model to a panel data set collected from two online retailers, we found that the strength of recommendations has a positive effect on sales. Moreover, this effect is moderated by the recency effect, where more recently released recommended items positively affect the cross-selling efforts of sellers. We also show that recommender systems help to reinforce the long-tail phenomenon of electronic commerce, and obscure recommendations positively affect cross-selling. We also found a positive effect of recommendations on prices. These results suggest that recommendations not only improve sales but they also provide added flexibility to retailers to adjust their prices. A comparative analysis reveals that recommendations have a higher effect on sales than does consumer feedback. Our empirical results show that providing value-added services, such as digital word of mouth and recommendations, allows retailers to charge higher prices while at the same time increasing demand by providing more information regarding the quality and match of products.

Key words and phrases: collaborative filtering, electronic commerce, e-tail, experience goods, recommender systems.

Web-based information technologies (ITs) enable Internet retailers to facilitate online customer interactions to enhance the shopping experience. A prominent example is digital word-of-mouth-based services, where shoppers can submit and share their feedback about products through reviews and rating systems on retailer Web sites. Internet retailers have also started analyzing online customer interactions to provide various value-added shopping services. Popular online retailers such as Amazon.com analyze data of various customer interactions, including their past purchases, ratings, and browsing patterns, as well as demographic and product information. Based on this, they then provide product recommendations to customers. Among the numerous methods for determining recommendations, algorithms based on collaborative filtering (CF) are the most popular among online retailers for recommending products [29, 39]. Recommendations from CF are determined by the levels of similarity of preferences among groups of consumers.

The importance of recommender systems has attracted significant academic interest. Research in this area focuses on developing and evaluating various recommendation algorithms. Most of the work has addressed the added value that these systems provide to consumers. A significant line of work has evaluated the predictive accuracy of recommendations in terms of reflecting the true preferences of users. In these studies, real preference data of customers are obtained from surveys or controlled field experiments and are then compared to the recommendations produced by various algorithms and systems [21, 23, 42]. Some studies (e.g., [30]) have focused on the ability to recommend relatively unknown items that would otherwise be missed by users. The rationale is that a system that routinely recommends popular or common items could yield a high measure of accuracy, but would be of little value to users.

Despite the growing evidence that recommender systems provide significant added value to users, there has been relatively little research (e.g., [2]) on their effectiveness in increasing sales for retailers who provide these services. One of the major reasons is the difficulty associated with measuring the impact of recommender systems on key performance indicators such as sales [24, 50]. It has been intuitively assumed that recommendations increase sales by providing high-quality, useful information to customers. However, customers may not trust recommendations whose rationale is not properly explained [47]. Moreover, along with recommendations, a typical product Web page of an online retailer includes information such as product features, images, expert reviews, customer reviews, and ratings. Each of these adds to information overload, and recommendations might easily become lost in the clutter. Thus, it is essential to analyze whether value-added services, such as online recommender systems, actually lead to increased sales.

The impact of recommender systems can be studied at various levels such as retailer, product category, or individual. This study intends to analyze their impact and effectiveness from the perspective of sales of individual items recommended by the system. Moreover, recommendations can be viewed as an add-on service bundled with the item of interest to provide more information on its quality, and it has been suggested that this could affect the retailer's pricing strategy [7]. Thus, in order to evaluate their effectiveness, it is essential to analyze their effect on two key business parameters—namely, sales and price. Developing an empirical method for evaluating the impact and effectiveness of recommendations is a nontrivial task, given the nature of CF algorithms. Development of such methods necessitates the incorporation of key dynamics that relate recommendations and sales. One such dynamic that was not considered by previous empirical studies is that recommendations may indirectly affect sales through pricing strategies. If retailers charge premiums for offering value-added recommender services, then eventually the increased prices would negatively affect demand. Ignoring the indirect effect of recommendations could lead to a biased inference regarding the impact of recommendation systems on sales.

Another important dynamic that has not been considered is the potential for simultaneity between recommendations and sales. In order to analyze the impact of recommendations on sales, prior empirical work determines how the strength of recommendations affects the sales of a recommended item [10]. Here, strength is measured in terms of the number of other items recommending that "base" item. That is, for a base item A, the recommenders are all other items that help to increase the popularity of item A by providing direct hyperlinks to its page. It is commonly assumed that strength of recommendations is exogenous when analyzing its effect on sales (e.g., [10]). However, the majority of recommender systems are based on CF, which utilizes data from both current and past sales. Thus, to the extent that recommendations drive sales, it follows naturally that sales would then affect the strength of recommendations. Therefore, strength of recommendations should be treated as an endogenous variable, influenced by sales, in order to eliminate an important source of bias in the estimation model. Methodologically, we develop a comprehensive measure of strength of recommendations. Unlike prior measures [10], our measure not only uses the number of recommenders (i.e., volume) but also includes the sales rank of recommenders (i.e., popularity) and the placement of the recommendation on a Web page (i.e., prominence of position) to determine strength. This type of method is successfully used by popular search engines such as Google to rank the results.

We use books as a product category and analyze the sales and recommendation data from the popular online retailer Amazon.com in order to study the impact of recommendations on sales. Our measure of strength of recommendations considers the number of items (see Figure 1) recommending a book, and also takes into account their popularity. Further, it accounts for the nature of the recommendation (i.e., whether it is offered as a pair with the recommender or shown as one of many related items). Because recommendations are prominently displayed when they are paired, such recommendations can have a potentially greater effect than do related recommendations.

Applying our model to a panel data set collected from two online booksellers, we found that the strength of recommendations received by a book has a significant positive effect on its sales. Moreover, this effect is moderated by the recency effect, where more recently released recommended items positively affect cross-selling efforts. We also show that recommender systems help in reinforcing the long-tail phenomenon of electronic commerce and obscure recommendations positively affect cross-selling. The impact of strength of recommendation on price is also significantly positive. Thus, strength of recommendations affects sales negatively through price as an intermediate variable. Overall, however, the net effect of strength of recommendations on sales is still significantly positive. Our analysis also confirms the simultaneity between sales and strength of recommendations. These findings facilitate understanding of how sales and strength of recommendations interact, and how this interaction is related to the pricing policy of retailers. The knowledge of how sales are affected by strength of recommendations, and how prices might be related to strength of recommendations, allows for unbiased measurement of the true effect of strength of recommendations

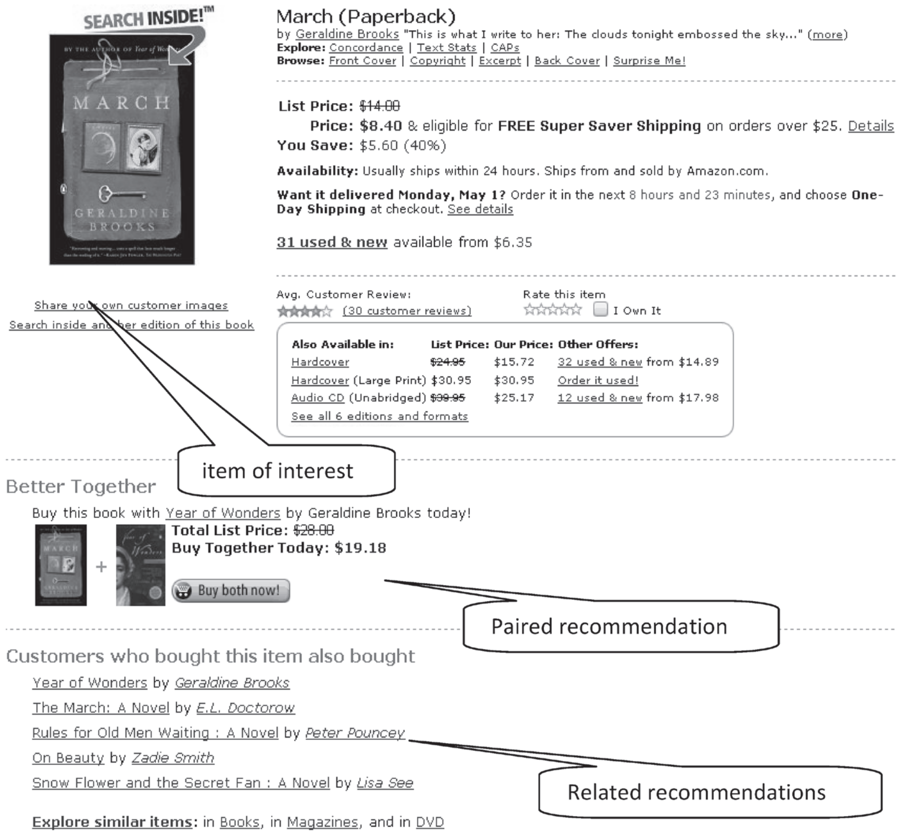

Figure 1. Screenshot of a Book Web Page on Amazon.com

on demand. It also allows managers to make better decisions concerning integration of recommender systems into their overall marketing strategies.

Theoretical Background and Research Hypotheses

Digital Word of Mouth

IT-INSPIRED CONSUMER FEEDBACK AND RECOMMENDATIONS assist consumers in evaluating the quality of items before making purchase decisions. The Internet provides an ideal platform for consumers to obtain and share quality information on products in various forms of digital word of mouth, such as online product ratings and reviews, social network sites, blogs, and so forth [13]. Digital word of mouth becomes more important in making purchase decisions when consumers have difficulty evaluating the quality of products. Such evaluation can occur either pre- or postpurchase. Prior research has classified products into three categories based on the ability of consumers to evaluate quality before or after purchase. The quality of *search goods* can be assessed easily prior to purchase. It is difficult to assess the quality of *experience goods* prior to purchase and usage, although it can be evaluated after one use. The quality of *credence goods* cannot be evaluated even after repeated purchase or use [3]. When making purchasing decisions for experience goods, in the absence of any prepurchase quality assessment, consumers usually turn to various sources of quality information on the product [32]. Empirical studies have shown the effect on demand of product information from various sources. These include pricing, where high prices serve as a signal of high quality for frequently purchased goods [9]; advertising as a direct source of characteristics of search goods [33]; and expert reviews, which have substantial influence on demand for experience goods [14, 37]. Prior studies have shown that Internet-enabled digital word of mouth also has a significant effect on consumer purchases. Chevalier and Mayzlin [12] found that the difference in the number of reviews received by books across two online retailers is positively correlated with the difference in the relative sales of the books across retailers.

Advances in ITs have also created new avenues for sellers to provide quality information to their customers. Sellers can analyze historical data and recommend products to induce them to take certain actions, such as visiting a product Web page or purchasing a product or service in accordance with their business objectives [45]. Sellers mainly use two types of recommendation systems—content based (i.e., attributes of the product) or CF based (behavior of the users) [27]. In content-based recommender systems, sellers recommend items similar to those a given user has preferred in the past, whereas in CF-based recommendations, sellers determine users whose preferences are similar to those of the given user and recommend items that they have liked. A growing number of online companies, including Amazon.com, Barnes & Noble, eBay, iTunes, Netflix, and Google News, use some variation of CF-based recommender systems. The resulting recommendations are similar to word-of-mouth recommendations [5, 49] because they are based on the preferences of like-minded consumers to generate recommendations to help individuals identify items that might be of interest [38]. Word of mouth is traditionally defined as informal communication between consumers about the ownership, usage, or characteristics of products, services, and sellers [48]. Such informal consumer-to-consumer recommendations are digitized on the Internet by means of consumer reviews and ratings, which provide signals to the users about the preferences of other like-minded customers. CF-based recommendations also provide feedback about product-related preferences from similar customers. For example, on Amazon.com, CF-based recommendation results are posted under the title "Customers who bought this item also bought" and serve an automated intermediary role for recommendations based on traditional word of mouth. As digital word of mouth does in the forms of ratings and reviews, CF-based recommendations provide signals to the users about the preferences of other like-minded customers. In these systems, recommendations are usually made based on a mixture of past purchasing or browsing behavior, characteristics of the items being considered, and demographic and personal preference information about shoppers [28, 40].

Compared to other forms of digital word of mouth, recommender systems have distinctive features. Most implemented systems derive recommendations from past purchasing data, which increases their objectivity. While reviews and ratings reflect the subjective opinions of shoppers, they can also be easily manipulated by users. For example, one can write a product review despite not having purchased or used the product. In contrast, recommendations are derived from the actual purchases of the product, and therefore present an information source that is less likely to be manipulated by anyone other than the retailers. One experimental study compared the effect of recommendations made from recommender systems to those of other consumers [41]. Interestingly, the results showed that recommender systems have a positive influence that outweighs the opinions of other consumers. On the other hand, because retailers have full control of what recommendations to make and how to present them, it is natural for shoppers to discount the credibility of seller-implemented recommender systems. This perception is further fueled by anecdotal evidence of retailers manipulating the outcomes of recommender systems [15, 31].

Direct Effect of Recommendations on Sales

Recommender systems are customer-centric since the business driver is customer value [26]. They can affect consumer purchases in various ways. First, as the source of quality-related information, recommendations reduce the uncertainty of the quality of recommended items. They also reduce search costs related to finding the products that fit [45], leading to purchase by customers who would otherwise not have done so. Thus, as an IT artifact [6], they serve as a support for purchase decision making [17] that can improve decision quality [49] by reducing the number of items to browse [20] and the time it takes to decide [22].

Second, they can increase cross-selling opportunities through signaling and advertisement effects. Prior purchases by other consumers may have strong signaling effects and, hence, influence purchase decisions. Recommender systems provide prominent Web page space to the list of recommended items. Such product exposure may persuade users to purchase products because of advertisement effects [46]. Recommender systems can even help those customers who are uncertain about their own taste to identify what their true favorites are. Recommendations also serve as advertisements, which tends to increase the awareness of relatively obscure items [4].

Third, recommender systems can help build customer loyalty and increase switching costs. As time goes by, retailers accumulate more and more data about customers and products and can provide more and more accurate recommendations, which makes it less appealing for a customer to switch to another seller due to the difficulty in the transfer of this knowledge. Overall, in all the above situations, their use should increase the overall sales of a seller. More specifically, the use of a recommender system should increase the sales of the recommended item, especially in the first and second situations. Moreover, the increased sales of the recommended item primarily depends on the strength of recommendations derived from the number of recommenders (i.e., volume), the popularity of the recommenders (i.e., sales rank), and the placement of recommendations (i.e., prominent position on a Web page). Hence,

Hypothesis 1: Strength of recommendation has a positive effect on sales of the recommended product.

Indirect Effect Through Price

The indirect effect of the strength of recommendations on sales is mediated through the retailer's pricing policy, which reflects not only the quality of the product but also the service level received by the buyer. The electronic market dramatically increases the variety of products available to shoppers. While this makes it easier for a shopper to find a product that matches his or her preference, it also increases the shopper's search cost [10, 44]. Certainly, a recommender system as a value-added service would increase the shopper's utility by reducing the search cost for fitting products. Furthermore, the recommendations received by a product can be considered to be an add-on, or information good in addition to the product. Thus, together they form a pure bundle [1], and some shoppers would be willing to pay a premium to receive such a bundle [7]. A similar argument is applicable to customer reviews and ratings, which can also be considered to be services to reduce uncertainty about the product's quality. In summary, add-on services such as recommendations, reviews, and ratings all increase customer utility by reducing search costs for quality-related information. Empirical studies on the use of shopbots have shown that some customers are willing to pay a higher price for such additional services [43]. In the case of recommendations, the more strongly a product is being recommended, the more customers will be convinced that it fits their tastes, therefore the more value is added to the product, and the more the retailer can charge.[1] Hence,

Hypothesis 2: Strength of recommendation has a positive effect on the price of the recommended product.

Product Characteristics

The effect of the strength of recommendations on sales could also be affected by product characteristics. Prior research has predominantly considered recency and obscurity as two of the important item characteristics that may moderate the effect of recommendations on sales. In the context of books, Chevalier and Mayzlin [12] suggest that books published in the prior years may have less popularity than recently published books. This popularity may drive the recency effect, where the effect of recommendation on sales is moderated by how long the item has been on the market. Recently introduced items in the market have more familiarity because they receive higher exposure, publicity, or reviews, and such familiarity may tend to reinforce the influence of recommendations on sales [21].

Novelty is another characteristic that may moderate the effect of recommendations on sales. Recommendations may add little value if they are obvious to the user. Novelty and serendipity are important features for evaluating the nonobvious nature of recommendations [21, 34]. These issues have also been discussed in the context of the long-tail effect of electronic commerce, where a large number of unique items are sold in smaller quantities in order to serve various market niches [4]. Oestreicher-Singer and Sundararajan [36] consider recommendations to be a hyperlinked network of products and show their role in distributing demand across various obscure items.

Thus, the effect of recommendations on sales is moderated both by recency effect and obscurity. Hence,

> *Hypothesis 3a: The recency of the recommended item has a positive moderating effect on the impact of strength of recommendations on sales.*

> *Hypothesis 3b: The obscurity of the recommended item has a positive moderating effect on the impact of strength of recommendations on sales.*

Sponsored Recommendations

Retailers may have incentives to manipulate recommender systems based on considerations such as inventory levels, sale policies, and revenue objectives. Online sellers such as Walmart.com have acknowledged human intervention in their recommender systems [19]. Likewise, Netflix has been integrating its inventory levels with the recommender systems, as a parameter affecting recommendation decisions, in order to optimize inventory turnover without affecting service levels [35].

Amazon.com offers a sponsored pairing program, where authors or publishers can have their books paired with other books, ideally best sellers, by paying monthly fees. For the consumer, these sponsored recommendations are hardly distinguishable from standard paired recommendations. Standard pairing is based on the CF-based algorithms, whereas sponsored pairing is done by the retailers for promotion-related or other economic purposes. Amazon.com does offer a discount if users purchase this sponsored paired recommendation. This phenomenon raises the interesting question of whether sponsored paired recommendations that are not CF-based have the same effect on sales as those that are CF-based. On the one hand, it is possible that sophisticated shoppers would realize that sponsored paired recommendations do not reflect the true quality and product fit, and therefore would ignore them. Moreover, any such manipulation affects the transparency of the recommender system. The role of transparency is very important for forming perceptions about the recommendations [18] and any such manipulation may be perceived negatively by the user. On the other hand, for the common user, it is not easy to determine whether the paired recommendation is organic or sponsored. Moreover, because Amazon.com usually provides an extra discount for these sponsored paired recommendations, they might prove to be more desirable to shoppers than CF-based paired recommendations. Hence,

> *Hypothesis 4: A retailer's use of sponsored pairing has a positive moderating effect on the impact of strength of recommendations on sales.*

Data Collection and Measurement

We use books as a category for testing our conceptual model because they are experience goods and are homogeneous across different retailers. Another reason is that recommendations for books are almost always other books, making it easier to construct a straightforward measure of recommendations. Further, books have been used by several other studies on digital word of mouth, allowing our results to be comparable to theirs. The recommendations generated by recommender systems can be based on either user-to-user CF, where the suggestions are functions of the purchases of customers considered to be similar to the current buyer, or on item-to-item CF, where the suggestions are made based on the relatedness between items [28]. In this research, we focus on those recommender systems that are based on item-to-item CF, which is used by Amazon.com, a pioneer in online retailing [28].

We chose Amazon.com and Barnesandnoble.com as the source of data collection. These two retailers account for nearly 90 percent of the online book retailing market [25]. Amazon.com alone accounts for more than 70 percent of the online book market and is a leader in developing and implementing various customer feedback and recommender systems that are later adopted by others. Amazon.com also provides sales rank information of all the books on its Web site, which enables us to derive sales quantity using a well-established methodology [12]. A screenshot of a Web page of the book *March* at Amazon.com is shown in Figure 1 in which two types of recommendations are provided. The first is under the title "Better together," where a single book is recommended with *March* as a pair. We term this *paired recommendation.* In Figure 1, *March* is a *paired recommender* of *Year of Wonders.* The second type of recommendation appears under the title "Customers who bought this item also bought" and is termed *related recommendations. March* is therefore a *related recommender* of these five books. Paired recommendations are usually displayed prominently on the product page. Sometimes, an extra discount is offered for purchasing a bundle of the recommender book with the paired recommendation item. In most cases, the paired recommendation is also the top item in the list of related recommendations. However, we do observe exceptions where the paired recommendation is from outside the list of related recommendations. Also available on this page and related to our data collection are price, average customer rating, number of reviews, and sales rank (not shown in Figure 1 due to the length of the Web page). Note that the lower the sales rank, the greater the corresponding sales quantity.

We limit our data collection to those books that are recommended by the 5,000 top-selling books (ranking 1–5,000) of each day during the data collection period. The reason for that is to improve the efficiency of data collection without losing generality. The focus of this study is the recommendations received by a book. We learned from the preliminary data collection that the additional number of recommenders of a book (i.e., from how many more books this book receives a recommendation) decreases with the sales rank of its recommenders. As we increase the search limit for recommenders, we find fewer and fewer additional recommenders, and the total number of recommenders flattens out at a certain point. In addition, according to the mapping method from rankings to sales, the 5,000 top-selling books account for 80 percent of the total book sales in any particular day. Therefore, we believe that this restriction will not affect the validity of the results.

It is worthwhile to point out that the sales ranks of our sample of base items range from 1 to 9,990. To assemble a random sample, we enumerated all books that were recommended by any of the top 5,000 books at Amazon.com on January 1, 2006. This yielded a list of 6,103 books, of which 500 were randomly chosen as the base items. We collected detailed data for these books for a period of 52 days. The data include price, average customer rating, number of reviews, sales rank, what books from the top 5,000 recommended that book on each day, and the sales ranks of all those recommenders. We also collected similar data from Barnesandnoble.com every day. Sometimes Amazon.com and Barnesandnoble.com did not carry the same book, resulting in missing data points. We dropped such observations with missing data points and used a balanced panel data. As a result, our final sample consists of a panel data set for 156 books for a period of 52 days. Our data collection scheme is shown in Figure 2.[2]

To estimate the effect of recommendations, it is desirable to construct a single measure that reflects the overall strength of the recommendations that a base item receives from all recommenders. In order to construct such a measure, we use a link structure analysis technique similar to the one used by popular search engines such as Google. Here, the strength of the recommendation is measured not only by how many recommenders recommend an item but also by the importance of those recommenders.

In general, strength of recommendations depends on the following:

1. *How many recommenders recommend a base item.* The more recommenders there are for a base item, the more likely shoppers with different interests would be led to it.
2. *How many copies of the recommenders are sold.* The more customers purchase the recommender, the more exposure the recommendation would get, hence the more likely the base item would be considered for purchase.
3. *The type of recommendation.* Is it through a paired recommendation, which is presented in a more noticeable way on Amazon.com, or a related recommendation, which is hidden in a list? It is intuitive to assume that a paired recommendation might have higher effect. Nevertheless, it is desirable to at least make a distinction between the two types of recommendations.[3]

Because sales quantity is not publicly available, we turn to the literature that develops models to derive sales quantity from sales rank [8, 11]. Using sales data from publishers and from experimentation, it has been found that there exists a Pareto relationship between sales rank and sales quantity of a book at Amazon.com of the following form:

$$quantity = \mu \times rank^{\beta}. \tag{1}$$

Estimations of the parameters are very comparable across studies and have been used directly by other studies (e.g., [16]). For the purpose of measuring the strength of recommendations, we adopt the estimates of Brynjolfsson et al. [8]. However, for

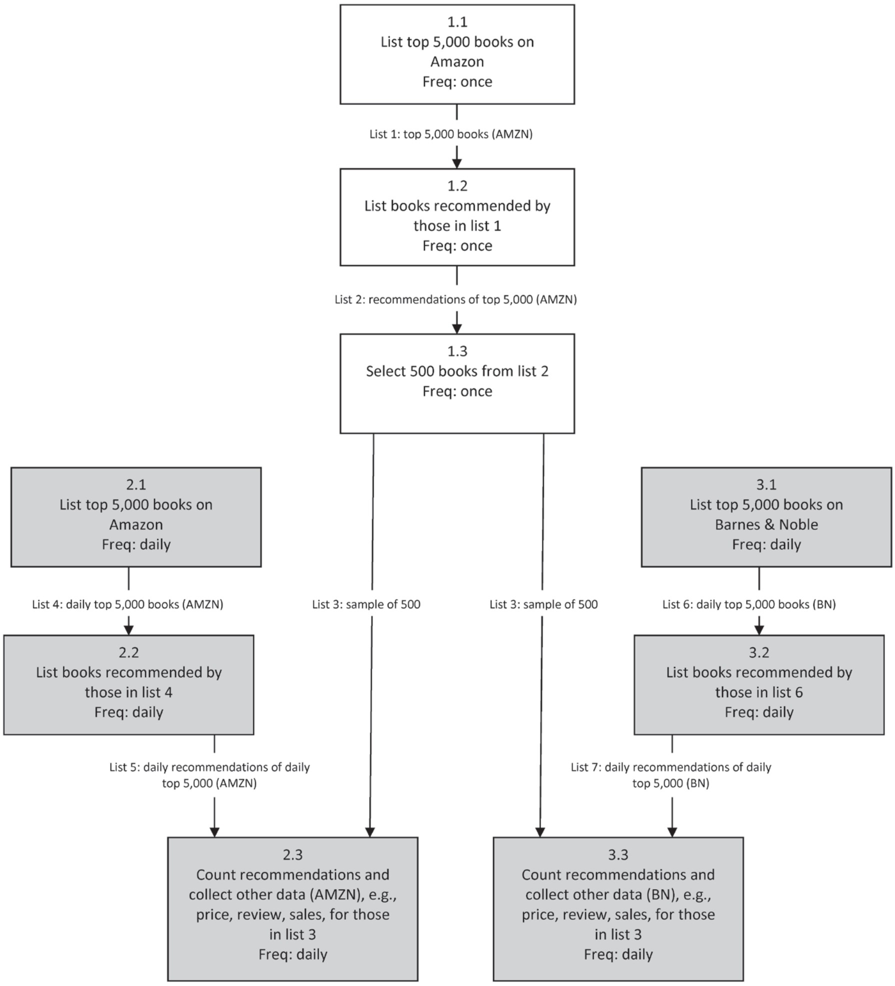

Figure 2. Data Collection Steps

the overall empirical model, we still use sales rank as a proxy for sales to avoid the possible bias caused by the mapping between rank and quantity.[4]

From the above observations, we have the following four measures of the overall strength of recommendations received by a recommended item: number of paired recommenders, total sales quantity of all paired recommenders, number of related recommenders, and total sales quantity of all related recommenders. The correlations between the four measures are shown in Table 1. We conducted a factor analysis on these four measures and found that they converged to one single underlying factor (with only one greater-than-one eigenvalue of 2.99 and the second-largest eigenvalue of 0.65). Therefore, we label the factor *strength of recommendations* and use the factor score as the measure of strength of recommendations in our later data analysis. The factor loadings of each measure and the standardized scoring coefficients are also listed in Table 1. Table 2 presents the definitions and descriptive statistics of all data items.

Table 1. Correlations Between Factor Measures and Results of Factor Analysis

Measures	Paired recommenders (number)	Paired recommenders (sales)	Related recommenders (number)	Related recommenders (sales)	Factor loading: strength of recommendations	Standardized scoring coefficient
Paired recommenders (number)					0.85	0.28
Paired recommenders (sales quantity)	0.56				0.84	0.26
Related recommenders (number)	0.90	0.52			0.87	0.27
Related recommenders (sales quantity)	0.59	0.92	0.67		0.89	0.30

Table 2. Definition and Descriptive Statistics

Data item	Definition	Mean	Median	Minimum	Maximum	Standard deviation
List price	List price of base item posted at Amazon.com	\$20.90	\$18.00	\$5.99	\$135.00	13.80
Price	Amazon.com selling price	\$14.22	\$12.89	\$4.39	\$85.05	8.26
Rating	Average number of stars	4.09	4	2	5	0.48
Reviews	Total number of reviews	308	73	2	5,140	734
Recent reviews	Number of reviews posted in time period *t*	0.67	0	0	135	3.84
Rank	Sales rank at Amazon.com	1,313	585	1	9,990	1,833
Number of paired recommenders	Total number of paired recommenders	2.5	2	1	12	1.9
Sales of paired recommenders	Total sales quantity of all paired recommenders	142	49	10	2,994	360
Number of related recommenders	Total number of related recommenders	5.1	3	1	31	5.1
Sales of related recommenders	Total sales quantity of all related recommenders	337	84	10	7,219	941
Competitor price	Selling price at Barnesandnoble.com	16.81	14.95	5.99	108	10.56

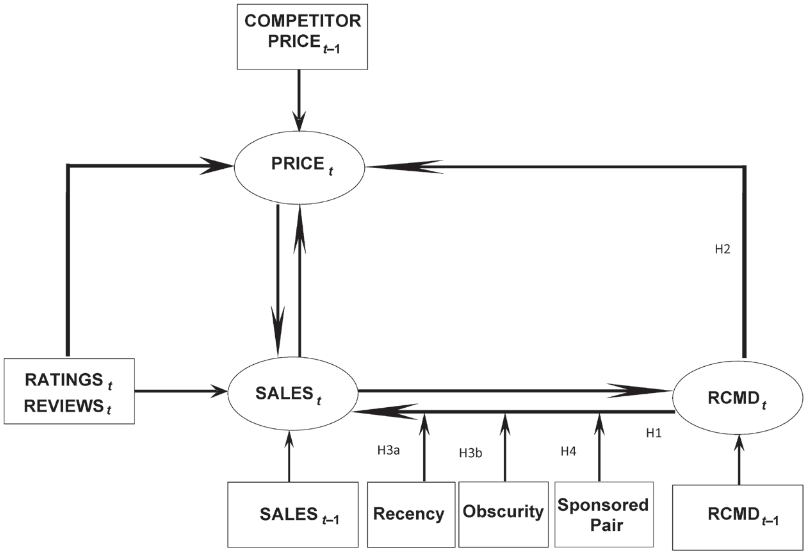

Figure 3. Empirical Model
Note: RCMD: strength of recommendations.

Research Model Specification

Our empirical model consists of three simultaneous equations with sales, price, and recommendation strength as dependent variables, and is illustrated in Figure 3. Ovals represent endogenous variables and rectangles represent exogenous variables. The first equation, with sales as the dependent variable, is based on the empirical model that is commonly used to study the effect of digital word of mouth on sales [10, 12]. We add strength of recommendations as an additional source of digital word of mouth that influences sales. Furthermore, individual book effects and time effects are incorporated in the model as follows:

$$\begin{aligned}\log rank_{it} &= \alpha_0 + \alpha_i^B + \alpha_t^T + \alpha_1 \log price_{it} + \alpha_2 rec_{it} \\ &+ \alpha_3 rating_{it} + \alpha_4 rev_{it} + \alpha_5 \log rank_{it-1} + u_{it},\end{aligned} \tag{2}$$

where log *rank* is the log of sales rank, log *price* is the log of Amazon.com's selling price, *rec* is the factor score for strength of recommendations, *rating* is the average star rating, *rev* is the number of recently added reviews, and *u* is a random shock term. The subscript *i* indexes each book in the sample and *t* indexes each day during the data collection period. We included a lagged dependent variable to capture the effect of all factors in the past that could have influenced sales but were not included in the model.

The demand for a book could be affected by its intrinsic qualities and other book-specific factors. Therefore, it is reasonable to assume that there exists an unobserved book-specific effect on sales, which can be represented by a book-specific intercept α_i^B. Sales could also be affected by some unobserved events that happened during the data collection period, which can be represented by a time-specific intercept α_t^T.

The effect of recommendations on sales can be moderated by the recency and obscurity of the book. In order to analyze the moderating effect of recency, we added an interaction variable between recommendation strength and recency of the book in Equation (2). For the purpose of this study, "recency" has been operationalized as a dummy variable whose value is one if the book has been published in the past year and zero otherwise. Likewise, in order to analyze the moderating effect of obscurity, we added an interaction variable between recommendation strength and popularity of the book in Equation (2). For the purpose of this study, "obscurity" has been operationalized as a dummy variable whose value is one if the sales rank of the book is more than 2,500 or zero otherwise. In order to test Hypothesis 4 and analyze the moderating effect of such human intervention in recommender systems, we added an interaction variable between recommendation strength and a dummy indicating whether a paired recommendation is sponsored in Equation (2). This dummy variable takes on value one if the book is ever recommended by a sponsored paired recommendation and zero otherwise. We also added main effect variables for recency, obscurity, and sponsored paired recommendations in Equation (2) to analyze their effect on sales.

Because the recommender systems we study make recommendations based on current and past sales, sales would affect strength of recommendations, leading to the endogeneity of recommendation in Equation (2). Furthermore, the pricing decisions of retailers are obviously affected by demand and their competitor's behavior. As discussed previously, a retailer's pricing strategy is also affected by the consideration of recommendations as an add-on to the recommended item. Therefore, a single equation model misses the simultaneity among demand, strength of recommendations, and price. For this reason, we add two more equations. First, we add the following equation to model the pricing decision made by the retailer:

$$\begin{aligned} \log price_{it} &= \beta_0 + \beta_i^B + \beta_t^T = \beta_1 \log rank_{it} + \beta_2 rec_{it} + \beta_3 rating_{it} \\ &\quad + \beta_4 rev_{it} + \beta_5 \log cprice_{it-1} + v_{it}, \end{aligned} \tag{3}$$

where *cprice* is the competitor's price (i.e., Barnes and Noble's price) and v is a random error term. We also include the possible book effect and time effect in the presentation. This equation implies that the retailer bases its pricing decision on demand and on the level of add-on service bundled with the book, including recommendations, customer reviews, and ratings. Because books are homogeneous goods and there is stiff price competition among online sellers, the retailer's pricing decision is also influenced by the competitor's price in the previous period.

Next, we add the following equation to capture the reinforcing effect of sales on strength of recommendations:

$$rec_{it} = \gamma_0 + \gamma_i^B + \gamma_t^T + \gamma_1 \log rank_{it} + \gamma_2 rec_{it-1} + w_{it}, \tag{4}$$

where w is a random error term and the book-specific and time-specific effects are included. This equation implies that the current strength of recommendation depends on the current period sales and all past sales, the effect of which is captured by recommendation strength in the previous period.

One may argue that our model does not include the simultaneity between number of recent reviews (*rev*) and sales. Prior researchers have addressed this causality-related issue between sales and reviews. Chevalier and Mayzlin [12] note that the causality between reviews and sales is not clear, as reviews predate sales on Amazon.com. We have operationalized *revs* as a number of reviews posted in time period t, which is relatively less vulnerable to causality. While the number of most recent reviews in time period t can affect the $rank_{it}$ of book i in time period t, $revs_{it}$ cannot be affected by the sales of book i in time period t, because posting of a review can happen only after the book is shipped and read.[5] Although we cannot rule out simultaneity between reviews and sales completely, our measure for number of reviews and analysis done by prior researchers [12] leads us to believe that causality between sales and reviews will not affect our results. Because we use a panel data set to estimate Equations (2), (3), and (4), we need to decide whether the book-specific and time-specific effects should be incorporated in all three equations. Alternatively, we can also incorporate a random effect into all three equations. Therefore, we conducted several tests to help decide the final specifications.

First, an F-test rejected the null hypothesis that there is no book-specific effect in all three equations. Furthermore, a Hausman specification test shows that a fixed book-specific effect is preferable to a random effect. The same tests could not reject the null hypothesis that there is no time-specific effect in all three equations. Therefore, the final specification of the system of equations excludes the time-specific effect term from all three equations. See Table 3 for various statistics.

To estimate this system of equations, a Hausman specification test reveals that three-stage least squares (3SLS) is more appropriate than simple ordinary least squares (OLS) estimation as shown in Table 4. Results based on the m-statistic confirm that 3SLS is preferred over OLS. The 2SLS results (not presented) are very consistent with the 3SLS results. In addition, by using time-demeaned values for all dependent and independent variables in Equations (2), (3), and (4), we do not need to estimate the book-specific intercept for all three equations. In time-demeaning, we subtract the mean value of each variable in our panel data from each individual value. This method removes the problem of time-constant unobserved heterogeneity. We also checked for multicollinearity and heteroskedasticity for all three equations and did not find any serious problems.

Results

Effect of Recommendations on Sales (H1)

Although our final empirical model is a system of three equations, we first present the results of pooled OLS regression of several variations of Equation (2) in Table 5 to show the effect of including and excluding certain independent variables. Specifically, we start with the baseline model and then add recommendation, lagged dependent variable, and book-specific fixed effects. The results are provided in four separate columns in Table 5. We also want to see the effect of simultaneity among sales, strength

Table 3. Results of Tests for Model Specifications

Equation	F-test for H_0: no book-specific effects	Hausman specification test for fixed versus random effects
Demand (2)	9.94	121.91
Price (3)	215	132.60
Recommendation (4)	8.94	447.82

Note: All items are significant at the $p < 0.0001$ level.

Table 4. Hausman Specification Test for Parameter Estimation Technique

Comparing	To	m-statistic	$\Pr > \chi^2$
OLS	2SLS	140	< 0.0001
OLS	3SLS	1,966	< 0.0001
3SLS	2SLS	–0.62	0

of recommendations, and price on the estimation of various coefficients. Our intention is to show that the estimation could be biased without strength of recommendation or without taking simultaneity into consideration. In summary, the results from various pooled OLS regressions show that strength of recommendation is an important variable, and that the fixed book-specific effects are essential for correct estimation.

Note that the results in column 4 of Table 5 could still be biased due to the endogeneity of price and strength of recommendations. The estimates from the system of three equations are presented in Table 6. The coefficient value for the strength of recommendations is negative, clearly supporting Hypothesis 1. Hence, strength of recommendations has a positive effect on the sales of a recommended item. The first column of estimates in Table 6 is for the demand equation with log of sales rank as the dependent variable. All coefficients are significant and have the expected signs. The values of the estimates are close to the corresponding ones in column 4 in Table 5. In summary, average rating, number of recent reviews, and strength of recommendations all positively affect the demand for a book.

Effect of Recommendations on Price (H2)

The estimates for the price equation, with log of price as the dependent variable, are shown in the second column in Table 6. The coefficient of the strength of recommendation variable is positive and, hence, we get full support for Hypothesis 2. This clearly shows that the retailer may increase the price of an item if it receives a higher level of strength of recommendation. The competitor's price in the previous period positively correlates with Amazon.com's current price, which is consistent with the nature of the market. The coefficient of log *rank* suggests that the higher the demand

Table 5. Pooled OLS Regression of Single Equation

	Dependent variable: log *rank*			
	(1)	(2)	(3)	(4)
Independent variables	Baseline model	Recommendation added	Recommendation and lagged dependent variable added	Recommendation, lagged dependent variable, and book effect added
Intercept	8.124***	7.88***	0.44***	All significant
	(0.186)	(0.15)	(0.06)	
log *price*	–0.088*	–0.002	0.01	0.53***
	(0.042)	(0.03)	(0.01)	(0.09)
Rating	0.246***	0.02	0.005	–0.08*
	(0.034)	(0.02)	(0.010)	(0.03)
Review	–0.567***	–0.36***	–0.02***	–0.006**
	(0.01)	(0.009)	(0.003)	(0.002)
Strength of recommendation		–0.93***	–0.06***	–0.15***
		(0.01)	(0.006)	(0.01)
log $rank_{t-1}$			0.94***	0.63***
			(0.004)	(0.009)
N	7,848	7,848	7,848	7,848
Adjusted R^2	0.30	0.53	0.95	0.96

Notes: Standard errors are shown in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 6. 3SLS Regression of System of Equations

Independent variables	Dependent variable log *rank*	log *price*	Recommendation
log *price*	4.12*** (0.74)	—	—
Rating	–0.14*** (0.04)	0.02** (0.004)	—
Review	–0.01*** (0.002)	0.0008*** (0.0002)	—
Recommendation	–0.13*** (0.02)	0.008*** (0.002)	—
log $rank_{t-1}$	0.61*** (0.01)	—	—
log *rank*	—	0.01*** (0.002)	–0.10*** (0.01)
log $cprice_{t-1}$	—	0.14*** (0.01)	—
$\text{Recommendation}_{t-1}$	—	—	0.63*** (0.009)
N		7,848	
Adjusted R^2		0.387	

Notes: Standard errors are shown in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

for a book, the lower the price Amazon.com tends to set. This might be explained by the nature of the market and competition as well. The intensity of competition across retailers for books that are in high demand could prompt Amazon.com to lower its price to compete with other sellers. When demand abates, Amazon.com might feel less competitive pressure, therefore making more room for higher prices. In addition, it is a common marketing practice to use a popular item as a "loss leader" to aggressively attract customers to the store and recover the loss by selling other profitable items to the same customer.

The positive coefficients for recommendations, along with those for reviews and rating, provide very interesting insights. As mentioned earlier, these value-added services could be considered to be add-on components bundled with the product. They are meant to provide signals of quality and fit to customers. If the book receives more recommendations, then it captures more "eyeballs" and more customers consider it a potential fit. This will not only increase the potential sales of that book but also makes it more likely that the retailer could recover the cost of providing recommendations by passing it on to the customer. Similarly, the more reviews and the higher rating a book receives, the more quality information is bundled with the book; hence, the more likely the customer would be willing to pay extra. This implies that retailers can use various customer feedback mechanisms to differentiate their products that are otherwise homogeneous across different sellers. These services even give retailers some room to charge a slightly higher price. However, how much premium can be charged is ultimately subject to the negative demand elasticity for price from the demand equation.

In the recommendation Equation (4) with strength of recommendations as the dependent variable, the coefficient of log *rank* in the third column in Table 6 strongly confirms the reinforcing effect of sales on strength of recommendations. Increased sales of the base item would increase its exposure to shoppers. If the base item is purchased along with other books, that increases the likelihood that the base item would be associated with other books as the result of the CF algorithm, which would increase strength of the recommendations received by the base item.

To gauge the comparative advantage provided by the comprehensive measure of the strength of recommendations, we also estimated the model using "number of recommendations" as a simpler measure of recommendation strength. Table 7 reports the 3SLS results with this simpler measure.[6] A comparison of these results to Table 6 shows consistency in sign and significance of the variables with both measures. However, using the comprehensive measure of the strength of recommendations enables us to explain and capture a higher degree of variance in the system. According to the factor analysis result for our construct of recommendation strength, one unit of change in number of recommendations causes a quarter unit of change in the factor score. Therefore, the coefficient –0.13 for recommendation in Table 6 should translate to –0.033 in Table 7, while the actual coefficient value in Table 7 is only –0.01. This suggests that using the simple measure does not capture the intrinsic differences among different types of recommendations, and therefore misrepresents the true effect.

To test the robustness of the above results, we replace sales rank with sales quantity derived from sales rank as an alternative measure of demand, and run the 3SLS on the system of equations. The coefficient estimates are consistent with those in Table 6 in terms of both direction and magnitude.

Effect of Book Characteristics (H3a and H3b)

Results of our analysis for studying the moderating effect of recency and obscurity are provided in Table 8. We find that the interaction effect between recommendation and recency is statistically significant. This shows that the effect of recommendations on sales is moderated by the recency effect, and if the recommended item is relatively new, then recommendations will have more influence on purchase decisions. We attribute this moderating effect to a few possible causes. First, recency effect could be the result of product familiarity. On Amazon.com, the majority of the top-selling books are recently published. Recent items have relatively higher exposure and publicity due to extensive coverage in the media and editorial reviews. Hence, consumers may be more familiar with recently released items. Product familiarity tends to reinforce the influence of the recommendations. Second, our sample does not consist of reference books, which are less vulnerable to time. Recency as a main effect is insignificant. This might be due to the fact that the majority of books in our sample are quite recent. This also shows that consumers are more likely to respond to those recent items that match their tastes better.

Table 7. 3SLS Regression of System of Equations (with Number of Recommendations)

Independent variables	Dependent variable: log *rank*	log *price*	Recommendation
log *price*	4.00***	—	—
	(0.74)		
Rating	–0.11***	0.01**	—
	(0.03)	(0.004)	
Review	–0.01***	0.0008***	—
	(0.001)	(0.0002)	
Number of recommendations	–0.01*	0.002**	—
	(0.005)	(0.0005)	
log $rank_{t-1}$	0.63***	—	—
	(0.01)		
log *rank*	—	0.01***	–0.21***
		(0.002)	(0.05)
log $cprice_{t-1}$	—	0.14***	—
		(0.01)	
Number of $recommendations_{t-1}$	—	—	0.50***
			(0.009)
N		7,848	
Adjusted R^2		0.29	

Notes: Standard errors are shown in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

As shown in Table 8, we find that the interaction effect between recommendation and obscurity is statistically significant. This suggests that online recommendations are more influential when the recommended books are not so obvious. Prior researchers have discussed the long-tail effect of electronic commerce where sellers sell large number of unique items in smaller quantities in order to serve various market niches [4]. Oestreicher-Singer and Sundararajan [36] consider recommendations to be a hyperlinked network of products, and show the role of recommendations in distributing demand across various obscured items. Prior research has also indicated that recommendations will be more valuable if the recommended items are novel and serendipitous [21, 34]. Our results confirm that online recommender systems do help in reinforcing the long-tail phenomenon of electronic commerce. Obscurity as a main effect is insignificant. This shows that recommendations play a dominant role in influencing the long-tail effect of electronic commerce.

Effect of Sponsored Paired Recommendations (H4)

Results of our analysis of the effect of the sponsored paired recommendations are provided in Table 8. We find that the interaction effect between recommendation and this dummy is statistically significant, suggesting that the sponsored paired recom-

Table 8. 3SLS Regression of System of Equations with All Interaction Effects

Independent variables	Dependent variable		
	log *rank*	log *price*	Recommendation
log *price*	3.99*** (0.74)	—	—
Rating	–0.11*** (0.04)	0.02*** (0.004)	—
Review	–0.01*** (0.002)	0.0008*** (0.0002)	—
Recommendation	–0.01 (0.03)	0.01*** (0.002)	—
log $rank_{t-1}$	0.59*** (0.01)	—	—
Recency	0.01 (0.01)	—	—
Interaction (recommendation and recency)	–0.19*** (0.03)	—	—
Obscurity	0.007 (0.009)	—	—
Interaction (recommendation and obscurity)	–0.34*** (0.03)	—	—
Sponsored	–0.001 (0.01)	—	—
Interaction (recommendation and sponsored)	–0.05** (0.01)	—	—
log *rank*	—	0.02*** (0.002)	–0.17*** (0.01)
log $cprice_{t-1}$	—	0.13*** (0.01)	—
$\text{Recommendation}_{t-1}$	—	—	0.62*** (0.009)
N		7,848	
Adjusted R^2		0.38	

Notes: Standard errors are shown in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

mendations do have a slightly higher effect on sales than regular recommendations. We attribute this moderating effect to a few possible explanations. First, the majority of sponsored paired recommendations are paired with the top-selling items. Because of increased exposure, sponsored paired items positively affect the impact of recommendation on sales. Second, sponsored paired recommendations are usually offered at additional discounts, which may make them more attractive to customers. Sponsored paired recommendations as a main effect is insignificant. This shows that sponsored pairing works better when the strength of recommendation is high.

Product Complementarities

While our results clearly show the effect of recommendation on sales, there is a possibility that this effect is not because of recommendations, but simply due to product complementarities. Certain products such as printers and printing cartridges, digital cameras and memory cards, and textbooks and student guidebooks are complements to each other. As more shoppers buy these complementary products together, CF-based recommender systems tend to start recommending the complementary items. To rule out complementarities as the cause of our empirical results, we performed a difference in difference analysis similar to one conducted by Chevalier and Goolsbee [11]. Our model consists of the same system of equations as Equations (2), (3), and (4) but with the value of each variable replaced by the difference between the corresponding values from Amazon.com and Barnesandnoble.com. For example, rec_{it} is defined as the difference of recommendation strength between Amazon.com and Barnesandnoble.com for book i at time t.[7] Results of our analysis are provided in Table 9. We find that recommendations have a positive effect on sales even after we tease out the possible complementarity between recommender and recommended item.

Conclusions

Measuring the effect of online value-added services such as recommender systems is a difficult task [24, 50]. In this research, we use an empirical approach to analyze the effect of online recommender systems on sales. We use a panel data set to keep track of the impact of recommendations on sales over the period of time. We build a simultaneous equation model to study the interaction among sales, recommendations, and retail prices and address certain endogeneity issues that may arise because of the nature of collaborative filtering-based algorithms. Our main focus is on the effect of recommendations on sales. Furthermore, we examine the effect of providing various value-added customer feedback services, such as recommendations and reviews, on retailer pricing decisions. In contrast to other studies on the same topic, our model introduces simultaneity among demand, price, and strength of recommendations, and therefore avoids potential bias in the inference. Even though the estimates from the single equation model and simultaneous equation model turn out to be close to each other using this data set, it is desirable to be able to separate the direct and indirect effects of various mechanisms on sales. For example, the direct effect of strength of recommendations could be overestimated if its indirect and negative effects through price are not explicitly modeled. Therefore, our empirical model provides more accurate estimation of the true effect of various customer feedback mechanisms on consumer demand.

In addition, a richer model such as ours can provide more insights into the interactions among demand, price, and strength of recommendations. These insights can help managers make better decisions regarding the marketing mix. Our empirical results show that providing value-added services, such as digital word of mouth and recommendations, allows retailers to charge higher prices, while at the same time increasing demand by providing more information regarding the quality and match of

Table 9. 3SLS Regression of System of Equations (Difference in Difference Analysis)

Independent variables	Dependent variable		
	log *rank*	log *price*	Recommendation
log *price*	0.26 (0.70)	—	—
Rating	–0.19*** (0.02)	–0.01* (0.007)	—
Review	–0.0006 (0.69)	0.001* (0.0006)	—
Recommendation	–0.047** (0.02)	0.007 (0.01)	—
log $rank_{t-1}$	0.28*** (0.01)	—	—
log *rank*	—	0.004 (0.016)	–0.03* (0.01)
log $cprice_{t-1}$	—	0.02** (0.008)	—
$\text{Recommendation}_{t-1}$	—	—	0.61*** (0.006)
N		27,785	
Adjusted R^2		0.20	

Notes: Standard errors are shown in parentheses. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

products. This provides guidance to management in deciding on the right combination of recommendations, promotions, and pricing strategies, which is not possible if using a single equation model.

In the online domain, consumers provide feedback about their product preferences and experiences to other consumers. This feedback could be explicit, as in descriptive reviews and ratings, or implicit, as in recommendations. Unlike reviews and ratings, where consumers provide direct feedback about the product, recommendations provide an indirect measure of the value of a product based on the common interest of the community. We found that strength of recommendations, along with number of reviews and average ratings, has a significant and positive effect on sales.

Online retailers can use strength of recommendations as one of the important factors for pricing and inventory-related decisions, especially for recent and obscure items. We found that the impact of recommendations on sales is moderated by the recency effect, where more recently released recommended items positively affect cross-selling efforts. Our results also show that recommender systems help in reinforcing the long-tail phenomenon of electronic commerce, and obscure recommended items positively affect retailers' cross-selling efforts. We also compare the difference in the effect among recommendations, reviews, and ratings. According to the factor analysis, one extra paired recommender would cause the factor score for strength of recommendations to increase by 0.247. Multiplying this by the regression coefficient of 0.13 for strength of recommendations from the demand equation, we get that, on average, one extra paired recommender could improve the sales rank by 3 percent. By similar calculation, it can be seen that, on average, one extra customer review would improve the sales rank by 1 percent. Although it would require different levels of effort to get one more recommender or to get one more review, so that the above comparison must be interpreted with specific cost information, our findings provide a starting point for decision making regarding the optimal combination of add-on services providing quality-related information to customers.

There can be various explanations for this difference between different types of digital word of mouth. First, ratings and reviews usually come from consumers having heterogeneous shopping patterns, whereas recommendations are based on the purchases of consumers with homogeneous shopping patterns. Second, retailers usually use an objective approach based on an automated algorithm to derive recommendations. Hence, they do not suffer from the possibility of dishonest feedback by phantom consumers. Third, recommendations are more useful to reduce the shopper's search cost for fit when facing a large variety of products. Reviews and ratings are useful when a shopper knows what he or she wants, but recommendations increase sales by cross-selling and by suggesting items of which a shopper is unaware. All of these benefits justify the investment in online recommender systems, and our empirical results prove that it is a valuable addition to the general digital word of mouth.

However, it is important to note here that retailers may have incentives to manipulate recommendations to fulfill their economic objectives. For example, Walmart.com admitted human intervention in its lists of related recommendations, and Amazon.com, in some instances, manipulates paired recommendations. By and large, these interventions and manipulations are obscured from consumers, and our analysis of the effect of the sponsored paired recommendations does find a slightly but significantly higher effect that can be attributed to those irregular recommendations. However, this could be due to other confounding effects such as additional discounts. Nevertheless, retailers should be careful while doing any manipulation with the results of recommendation systems, because consumers may become apprehensive about recommendations if they become aware of such manipulations.

But the lack of negative effect of irregular recommendations might be good news for retailers. That means retailers could use recommendations as a means of "quiet" promotion without hurting the trustworthiness of recommendations in the shopper's perception, as long as they keep such incidents at a minimal level. Furthermore, retailers might consider a dynamic pricing mechanism for promotions based on the popularity of the recommendation spot. Our empirical results on the effect of recommendations on sales could provide a good starting point in designing such a pricing scheme.[8]

Although our study provides useful insights, its limitations suggest interesting opportunities for future research. First, our empirical analysis only studies the recommendations of Amazon.com. Some retailers adopt different types of recommendation approaches, such as content-based or hybrids of content-based and CF approaches, and it will be worthwhile to analyze and compare the effect of various types of recommendations. On the other hand, Amazon.com is the pioneer in development and implementation of recommendations and many retailers follow Amazon.com's recommendation methods. Second, our analyses are limited to experience goods such as books. Recommendations may not be as influential in other product categories, such as consumer electronics, where descriptive and detailed reviews may have more persuasive power than recommendations. It will be interesting to see how recommendations affect sales of other product categories. Third, for some analyses, even though Amazon.com's ranking methodology might have changed, we have mapped sales ranks to sales based on parameters derived in studies conducted before the change took place.[9] Because of this, our analysis might not provide the exact effect of recommendations on sales. However, the Pareto relationship between sales rank and sales should remain true even after the change in the ranking method. Hence, our results remain valid even if we may have used slightly outdated parameter estimates. Fourth, we could extend this research to solve the retailer's decision problem to determine the degree and effect of recommenders for various products.

Notes

1. If recommendations are manipulated by the seller, then the relationship between price and the strength of recommendation can be bidirectional. As the majority of the recommendations are system generated, we exclude this possibility.

2. Only books that were stocked by both Amazon.com and Barnesandnoble.com during the entire time period were included in our data set. Apart from this, our automated agent missed collecting data for some books on some days because of connectivity issues. These issues can be attributed to time-out errors, server-side issues, or network-related issues.

3. Some retailers (e.g., Barnesandnoble.com) do not offer paired recommendations. In such cases, our strength of recommendation measure will only consider related recommendations.

4. To test the robustness of the results, we ran the three-stage least squares (3SLS) regression using sales quantity instead of sales rank and found similar results.

5. Standard delivery time for books from Amazon.com is around 3 to 5 days and minimum delivery time is at least 24 hours.

6. OLS results for this measure are not included for the sake of brevity. However, they are also consistent in sign and significance.

7. Our original data set did not have comprehensive data for Barnesandnoble.com. In order to perform difference in difference analysis, we collected data again in June 2008. As Barnesandnoble.com does not provide paired recommendations, we adjusted the measurement of recommendation strength to incorporate only related recommendations.

8. Currently, Amazon.com charges a flat fee for placing a book at any recommendation spot.

9. Amazon.com has started considering the sales of used books in calculating sales ranks [16].

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