# Empirical Analysis of the Business Value of Recommender Systems

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**Empirical Analysis of the Business Value of Recommender Systems**

**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 that serve to reduce consumer search costs and uncertainty associated with the purchase of unfamiliar products. The central question we address is the business value of online recommender systems to online retailers. We develop a robust empirical method that incorporates indirect impact 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 impact on sales. We also found empirical evidence for the reinforcing effect of sales on recommendations and for the positive impact of recommendations on prices. These results suggest that recommendations not only improve sales but also provide added flexibility to retailers to adjust their prices. A comparative analysis reveals that recommendations have a higher impact on sales than consumer feedback. Our study demonstrates the value provided by information technology to an online retailer and provides guidelines for integrating recommender systems into their overall marketing strategy.

Keywords: Recommender Systems; Digital Word of Mouth; Electronic Commerce; Collaborative Filtering; Experience Goods; System of Equations.

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## 1. INTRODUCTION

Net-based information technologies enable online retailers to provide new services to enhance customer experience and to increase sales. Shoppers have long been able to submit and share their feedback about products through review and rating systems on retailer websites. In recent years, online recommender systems have become another popular service offered by many online retailers. These systems utilize data on customers' past purchases, ratings, and browsing patterns, as well as demographic and product information to suggest "recommended items" that is related to a given "item of interest". The recommendations generated by these systems can be based on either user-to-user collaborative filtering, where the suggestions are functions of the purchases of customers considered to be similar to the current buyer, or on item-to-item collaborative filtering, where the suggestions are made based on the relatedness between items (Linden et al. 2003). In this research, we focus on those recommender systems that are based on item-to-item collaborative filtering since they constitute the majority of recommender systems in use.

Most of the previous work has addressed the value added that these systems provide to consumers. A significant line of work has evaluated the predictive accuracy of recommendations in terms of reflecting the users' true preferences. In these studies, real preference data of customers are obtained from surveys or controlled field experiments and then are compared with the recommendations produced by various algorithms and

1 systems (Herlocker et al. 2004; Konstan et al. 1997; Shardanand and Maes 1995). Some

2 studies (Mobasher et al. 2001) have focused on the ability to recommend relatively

3 unknown items that would otherwise be missed by the users. The rationale is that a

4 system that routinely recommends popular or common items could yield a high measure

5 of accuracy, but would be of little value to the users.

6 Despite the growing evidence that recommender systems provide significant value added

7 to the users, research on their business value to the retailers who provide these services is

8 nascent (Adomavicius and Tuzhilin 2005). It has been intuitively assumed that providing

9 recommendations would increase sales by providing high quality, useful information to

10 customers. Chen et al. (2004) studied the impact of the number of recommendations

11 along with the number of reviews and the quality of the ratings, on the sales of books at

12 Amazon.com. Utilizing cross-sectional data, they found that both the strength of

13 recommendations (measured by the number of recommendations of a book) and the

14 number of reviews that a book receives have significant positive impacts on the sales of

15 the book.

16 The purpose of the current work is to develop a robust empirical method to evaluate the

17 relationship between recommendations and sales. Development of such methods

18 necessitates the incorporation of key dynamics that relate recommendations and sales.

19 One such dynamic that is not considered by previous studies is that the strength of

20 recommendations could have an indirect impact on sales through a retailer's pricing

21 strategy. Recommendations can be viewed as an add-on service bundled with the item of

22 interest to provide more information on its quality. Since a retailer provides this

1    additional service to the consumers, it has been suggested that retailers might charge

2    higher prices for this service (Bergemann and Ozmen 2006). Eventually the increased

3    price would affect demand in a negative way. Ignoring this indirect impact of

4    recommendations could lead to a biased inference regarding the impact of

5    recommendation systems on sales.

6    Another important dynamic, that has hitherto not been considered, is the potential for

7    simultaneity between recommendations and sales. It is commonly assumed that strength

8    of recommendations is exogenous when analyzing its impact on sales (e.g., Chen et al.

9    2004). However, the majority of recommender systems are based on collaborative

10    filtering, which utilizes data from both current and past sales. Thus, to the extent that

11    recommendations drive sales, it follows naturally that sales would then impact the

12    strength of recommendations. Therefore, strength of recommendations should be treated

13    as an endogenous variable influenced by sales in order to eliminate an important source

14    of bias in the estimation model.

15    Methodologically, we also contribute by developing a comprehensive measure of

16    strength of recommendations. This measure of considers the number of 'base' items (see

17    Figure 1) recommending a book and  also takes into account the popularity of the base

18    books from which the recommendations come. Further, it accounts for the nature of the

19    recommendation (i.e., whether the recommendation is 'paired' with the book or only

20    'related' to it), since paired recommendations are more prominently displayed and can

21    therefore have a potentially larger impact than only related recommendations.

Applying our model to a panel data set collected from two online book sellers, we found that strength of recommendations received by a book does have significant and positive impact on its sales. On the other hand, 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 impact of strength of recommendations on sales is still significant and positive, and there exists a strong reinforcing effect of sales on strength of recommendations. We also demonstrate that our comprehensive measure of the strength of recommendations better captures the underlying phenomena than simply the number of recommendations.

These findings facilitate understanding of how sales and strength of recommendations interact, and how this interaction is related to a retailer's pricing policy. The knowledge of how sales are affected by strength of recommendations and how prices might be related to strength of recommendations allows unbiased measurement of the true impact of strength of recommendations on demand. It also allows managers to make better decisions concerning integration of recommender systems into their overall marketing strategies.

The remainder of the paper proceeds as follows. Section 2 provides a theoretical background and literature review on the influence of online consumer feedbacks and recommender systems, and develops a set of research propositions. Section 3 discusses our data collection and measurement. Section 4 presents our research models and the estimation methods. Section 5 presents our empirical results. Section 6 concludes with discussions, limitations, and potential future research.

## 2. THEORETICAL BACKGROUND AND RESEARCH PROPOSITIONS

**Digital Word of Mouth**

Nelson (1970) classifies products into two categories: search goods and experience goods. Consumers can predetermine the quality of search goods based on product specifications before purchasing. However, the quality of experience goods can only be ascertained after their consumption. When making purchasing decisions for experience goods, consumers usually turn to various sources for quality information on the product. Empirical studies have shown the impact on demand of product information from various sources such as: pricing (Caves and Greene 1996); advertising (Nelson 1974); and expert reviews (Eliashberg and Shugan 1997; Reinstein and Snyder 2005).

The Internet provides an ideal platform for consumers to obtain and share quality information on products in various forms of digital word of mouth (Dellarocas 2003). Chevalier and Mayzlin (2004) examine the impact of online consumer feedbacks on book sales. They found that the difference in the number of reviews received by books across two online retailers leads to the difference in the relative sales of the books across retailers. Gopal et al. (2006) study whether the sales of music is impacted by peer-to-peer music sharing and show that online music sharing has a positive impact on sales of high quality music by providing consumers a way of sampling before purchasing.

The Internet also makes available another popular source of quality related information, i.e. recommendations produced by various online recommender systems. Since the first well known recommender system, Tapestry, came into being more than a decade ago (Goldberg et al. 1992), recommender systems are increasingly being used in electronic

1    commerce. Recommender systems help individuals identify items that might be of

2    interest to them, from a large collection of items, by aggregating inputs from all

3    individuals (Resnick and Varian 1997). Early recommender systems were operated by

4    third parties that were not selling the underlying items, such as GroupLens for Usenet

5    articles (Konstan et al. 1997), PHOAKS and SiteSeer for URLs (Rucker and Polanco

6    1997; Terveen et al. 1997), etc. However, more and more online retailers are

7    implementing recommender systems on their websites to suggest items to shoppers. In

8    these systems, recommendations are usually made based on a mixture of past purchasing

9    or browsing behavior, characteristics of the items being considered, and demographic and

10   personal preference information of shoppers (Linden et al. 2003; Schafer et al. 2001).

11                          **Direct Impact of Recommendations**

12   It is argued that recommender systems help increase sales by converting browsers into

13   buyers, increasing cross-sell opportunities, and building customer loyalty (Schafer et al.

14   2001). The abundance of products and product-related information available online

15   makes it harder for shoppers to choose the one that best fits their tastes and needs, thus

16   increasing the search cost for fit (Chen et al. 2004). Online recommender systems can

17   help shoppers identify those products that are related to their current interests from the

18   huge collection of available products, thereby reducing the cost of processing product-

19   related information. From this perspective, it is expected that strength of

20   recommendations would positively affect the sales of the books being recommended.

21   On the other hand, the credibility of recommender systems is also an important factor in

22   determining the impact of the strength of recommendations on sales. Recommendations

1    can influence shoppers' decisions only when they are perceived to be objective and

2    credible. Since retailers have full control of what recommendations to make and how to

3    present them, it is natural for shoppers to discount the credibility of online recommender

4    systems because of potential manipulation (i.e. recommendations that deviate from the

5    outcomes generated by the collaborative filtering algorithms) by retailers. This perception

6    is further fueled by anecdotal evidence of retailers manipulating the outcome of

7    recommender systems (Flynn 2006; Mui 2006).

8    Nevertheless, the fact that most online recommender systems derive recommendations

9    from past purchasing data of all shoppers using collaborative filtering based algorithms

10    does increase the objectivity of recommendations, compared to other customer feedback

11    mechanisms such as reviews and ratings. While reviews and ratings reflect the subjective

12    opinion of shoppers, they could also be easily manipulated by individual users. For

13    example, one can write a product review despite not having purchased or used the

14    product. In contrast, recommendations are derived from the actual purchases of the

15    product, and therefore present an information source that is less likely to be manipulated

16    by anyone other than retailers themselves. One study using experimentations compared

17    the impact of recommendations made by recommender systems and that by other

18    consumers (Senecal and Nantel 2004). Interestingly, the results showed that

19    recommender systems do have an influence on consumer's choice of a product, and are

20    more influential than other consumers' opinions.

21    Finally, given the richness of the information that is already available on a webpage for a

22    product, a recommendation might easily get lost among all the other information such as

1    product specifications, customer reviews, and ratings. Therefore, whether

2    recommendations can catch the shopper's attention needs to be verified empirically.

3    Following the findings of previous studies, we propose that:

4    *Proposition 1: Higher level of recommendation strength has a positive impact on sales.*

5                              **Indirect Impact on Price**

6    The indirect impact of the strength of recommendations on sales is mediated through the

7    retailer's pricing policy, which reflects not only the quality of the product but also the

8    service level received by the buyer. The electronic market dramatically increases the

9    variety of products available to shoppers at any store. While this makes it more likely for

10   a shopper to find a product that better matches her preference, it also increases the search

11   cost for the same shopper to find a product that fits her requirements (Stiglitz 1989).

12   Certainly a recommender system as a value-added service would increase the shopper's

13   utility by reducing the search cost for fitting products, and some shoppers would be

14   willing to pay a premium to receive recommendations to reduce uncertainty. A similar

15   argument is applicable to customer reviews and ratings as well, which can be considered

16   to be services to reduce the uncertainty about the product's quality. In summary, add-on

17   services like recommendations, reviews, and ratings all increase customer utility by

18   reducing the search cost for quality related information. Empirical studies on shopper

19   behavior at shopbots have shown that some customers are willing to pay a higher price

20   for such additional services (Smith and Brynjolfsson 2001). In the case of

21   recommendations, the more strongly a product is being recommended, the more

1   customers will be convinced that this product fits their tastes, therefore the more value is

2   added to the product, and the more the retailer can charge. Hence,

3   *Proposition 2: Higher level of recommendation strength has a positive impact on price.*

4                 **Simultaneity of Recommendations and Sales**

5   The frequency of consumer purchases of a given set of items is an important criterion

6   used in collaborative filtering algorithms to offer recommendations. Thus a

7   recommendation offered by an item of interest suggests to consumers that others who

8   have purchased the same item of interest have also purchased the recommended item

9   with relatively high frequency. To the extent that recommendations are effective in

10  generating additional sales, it follows logically that an additional increase in the sales of

11  the recommender would also increase the sales of the recommended item. This serves to

12  further enhance the strength of recommendation relationship between the two items.

13  Hence, we propose that there exists a reinforcing effect of sales on strength of

14  recommendations as follows,

15  *Proposition 3: Higher level of sales has a positive impact on recommendation strength.*

16             **3.  DATA COLLECTION AND MEASUREMENT**

17  We use books as a category for testing our conceptual model because they are experience

18  goods and are homogeneous across different retailers.  Another reason for using books is

19  that recommendations for books are almost always other books, making it easier to

20  construct a straightforward measure of recommendations in our study.  Further, books

1    have been used by several other studies on digital word-of-mouth, allowing our results to

2    be comparable to the other studies.

3    We chose Amazon.com and Barnesandnoble.com, the two biggest online book sellers, as

4    the source of data collection. These two retailers account for nearly 90% of the online

5    book retailing market (Latcovich and Smith 2001). Amazon.com, alone counts for more

6    than 70% of the online book market, and is a leader in developing and implementing

7    various customer feedback and recommender systems that are later adopted by others.

8    Amazon.com also provides sales rank information of all the books on its website, which

9    enables us to derive the sales quantity using a well-established methodology (Chevalier

10   and Mayzlin 2004).

11   A screen shot of a webpage of the base book, "March", at Amazon.com is shown in

12   Figure 1 in which two types of recommendations are provided. The first is under the title

13   "Better together", where a single book is recommended with the base book as a pair. We

14   term this *paired recommendation*. In Figure 1 "March" is a *paired recommender* of "Year

15   of Wonders". The second type of recommendations that is provided under the title

16   "Customers who bought this item also bought" is called *related recommendations*.

17   "March" is therefore a *related recommender* of these five books.

18   Paired recommendations are usually displayed prominently and include a picture of the

19   book cover as opposed to related recommendations, which are in a less prominent

20   position without pictures displayed. Sometimes, an extra discount is offered for

21   purchasing a bundle of the base book with the paired recommender. In most cases, the

22   paired recommendation is also the first in the list of related recommendations. However,

we do observe exceptions where the paired recommendation is from outside of 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 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 top 5,000-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 top-5,000 selling books account for 80% of the total book sales in a particular day. Therefore, we believe that this restriction would not affect the validity of the results. It is worthwhile to point out that the sales ranks of our sample of base books range from 1 to 9,990. This can be seen from the following discussion of random sampling.

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 books were randomly chosen as the base sample. We collected

1 detailed data for these books for a period of 52 days. The data include price, average

2 customer rating, number of reviews, sales rank, what books from the top-5000

3 recommended that book on that day, and the sales ranks of all those recommenders. We

4 also collected similar data from Barnesandnoble.com every day. Sometimes both

5 Amazon.com and Barnesandnoble.com did not carry the same book, resulting in missing

6 data points. Since our research model is based on a panel data set, we decided to drop all

7 missing data points to make the estimation straightforward. As a result, our final sample

8 consists of a panel data set for 156 books for a period of 52 days.

9 For the sake of estimating the impact of recommendation, it is desirable to construct a

10 single measure that would reflect the overall strength of the recommendations that a base

11 item receives from all recommenders. In general, strength of recommendations depends

12 on:

13 1) How many recommenders are recommending a base item? The more recommenders

14 there are for a base item, the more likely that shoppers with different interests would be

15 led to the base item.

16 2) How many copies of the recommenders are sold? The more customers purchase the

17 recommender, the more exposure the recommendation would get, hence the more likely

18 the base item would be considered for purchase.

1    3) What is the type of recommendation? Is it through a paired recommendation, which is

2    presented in a more noticeable way with a picture of the book cover on Amazon.com[1], or

3    a related recommendation, which is hidden in a list? It is intuitive to assume that paired

4    recommendation might have higher impact. Nevertheless, it is desirable to at least make a

5    distinction between the two different types of recommendations.

6    Since sales quantity is not publicly available, we turn to the literature that develops

7    models to derive sales quantity from sales rank (Brynjolfsson et al. 2003; Chevalier and

8    Goolsbee 2003). Using sales data from publishers and from experimentation, it has been

9    found that there exists a Pareto relationship between sales rank and sales quantity of a

10   book at Amazon.com in the following form:

11   $$quantity = \mu \bullet rank^{\beta} \tag{1}$$

12   Estimations of the parameters are very comparable across studies and have been used

13   directly by other studies (Ghose et al. 2006). For the purpose of measuring the strength of

14   recommendations, we adopt the estimates of Brynjolfsson et al. (2003). However, for the

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[1] Sometimes Amzon.com offers an additional discount for the bundle of the base item and the paired recommendation. Since this happens only to a very small portion of our sample, we did not consider it in the construction of the measure.

1    overall empirical model, we still use sales rank as a proxy for sales to avoid the possible

2    bias caused by the mapping between rank and quantity[2].

3    Based on the above observations, we have the following four measures of the overall

4    strength of recommendations received by a base item: number of paired recommenders;

5    total sales quantity of all paired recommenders; number of related recommenders; and

6    total sales quantity of all related recommenders. The correlations between the four

7    measures are shown in Table 1.We conducted a factor analysis on these four measures

8    and found that they converged to one single underlying factor. Therefore, we label the

9    factor *strength of recommendations* and use the factor score as the measure of strength of

10   recommendations in our data analysis. Table 2 presents the definitions and descriptive

11   statistics of all data items.

12   ## 4.  RESEARCH MODEL SPECIFICATION

13   Our empirical model consists of three simultaneous equations with sales, price, and

14   recommendation strength as dependent variables, respectively, and is illustrated in Figure

15   2. Ovals represent endogenous variables and rectangles exogenous variables. The first

16   equation, with sales as dependent variable, is based on the empirical model that is

17   commonly used to study the impact of digital word of mouth on sales (e.g., Chen et al.

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[2] To test the robustness of the results, we run the 3SLS regression using sales quantity instead of sales rank. The results are very consistent as shown in Table 7.

1    2004; Chevalier and Mayzlin 2004). We add strength of recommendations as an

2    additional source of digital word of mouth that influences sales. Furthermore, individual

3    book effects and time effects are incorporated in the model as follows.

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

5                                                                                              (2)

6    where log *rank* is the log of sales rank, log *price* the log of Amazon.com selling price, *rec*

7    the factor score for strength of recommendations, *rating* the average star rating, *rev* the

8    number of recently added reviews, and *u* a random shock term. Subscript *i* indexes each

9    book in the sample and *t* indexes each day during the data collection period. We included

10   a lagged dependent variable to capture the effect of all factors in the past that would have

11   influenced sales but were not included in the model.

12   The demand for a book could be impacted by its intrinsic qualities and other book-

13   specific factors.  Therefore, it is reasonable to assume that there exists an unobserved

14   book specific effect on sales, which could be represented by a book-specific intercept $\alpha_i^B$.

15   The sales could also be affected by some unobserved events that happened during the

16   data collection period, which could be represented by a time-specific intercept $\alpha_t^T$.

17   As discussed earlier, not only does strength of recommendations affect demand, but sales

18   might affect strength of recommendations as well, due to the collaborative filtering based

19   algorithm used by most recommender systems. Furthermore, the pricing decisions of

20   retailers are obviously affected by demand and competitor's behavior. Therefore, a single

17

1      equation model misses the simultaneity among demand, strength of recommendations,

2      and price. For this reason, we add two more equations as follows.

3      First we add the following equation to model the pricing decision made by the retailer.

4 $$\log price_{it} = \beta_0 + \beta_i^B + \beta_t^T + \beta_1 \log rank_{it} + \beta_2 rec_{it} + \beta_3 rating_{it} + \beta_4 rev_{it} + \beta_5 \log cprice_{it-1} + v_{it}$$

5 $$(3)$$

6      Here *cprice* is the competitor's price and *v* is a random error term. We also include the

7      possible book effect and time effect in the presentation. This equation implies that the

8      retailer bases its pricing decision on demand and on the level of add-on service bundled

9      with the book including recommendations, customer reviews, and ratings. Since books

10      are homogeneous goods and there is a stiff price competition among online sellers, the

11      retailer's pricing decision is also influenced by the prices of the competitor's price in the

12      previous period.

13      Next we add a third equation to capture the reinforcing effect of sales on strength of

14      recommendations by the following:

15 $$rec_{it} = \gamma_0 + \gamma_i^B + \gamma_t^T + \gamma_1 \log rank_{it} + \gamma_2 rec_{it-1} + w_{it} \qquad (4)$$

16      where *w* is a random error term and the book-specific and time-specific effects are

17      included. This equation implies that the current strength of recommendation depends on

18      the current period sales and all past sales, the impact of which are captured by the

19      recommendation strength in the previous period.

20      Since we use a panel data set to estimate (2) – (4), we need to decide whether the book-

21      specific and time-specific effects should be incorporated in all three equations.

18

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.

To estimate this system of equations, a Hausman specification test reveals that three-stage least square (3SLS) is more appropriate than two-stage least square (2SLS) estimation. In addition, by using time-demeaned values for all dependent and independent variables in (2) - (4), we do not need to estimate the book specific intercept for all three equations. We also checked for multicollinearity and heteroskedasticity for all three equations, and did not find any serious problems.

## 5. RESULTS

Although our final empirical model is a system of three equations, we first present the results of pooled OLS regression of several variations of (2) in Table 3, to show the impact of including and excluding certain independent variables. We also want to see the impact of simultaneity among sales, strength of recommendations, and price on the estimation of various coefficients. Our intention is to show that the estimation could be

1   biased without strength of recommendation or without taking simultaneity into

2   consideration.

3   Column (1) in Table 3 shows the estimates without recommendation and lagged rank as

4   independent variables. Since the dependent variable is rank, the negative price elasticity

5   is counter-intuitive. The positive coefficient for average customer rating contradicts the

6   findings of past research on digital word of mouth (Chevalier and Mayzlin 2004).

7   However, after adding strength of recommendation (as shown in column (2)) and lagged

8   rank (as shown in column (3)), both coefficients become insignificant. After adding fixed

9   book-specific effect (column (4)), all coefficients are significant and have the expected

10   signs. All fixed book-specific effects in column (4) are significant. Strength of

11   recommendation has significant impact across the last three columns although the

12   magnitude drops significantly after the lagged dependent variable is added. In summary,

13   the results from various pooled OLS regressions show that strength of recommendation is

14   an important variable and that the fixed book-specific effects are essential for correct

15   estimation.

16   Note that the results in column (4) of Table 3 could still be biased due to the endogeneity

17   of price and strength of recommendations. The estimates from the system of three

18   equations are presented in Table 4.

19   The first column of estimates in Table 4 is for the demand equation with log of sales rank

20   as the dependent variable. All coefficients are significant and have the expected signs.

21   However, the values of the coefficients are different from the corresponding estimates

1   from column (4) in Table 3. In summary, average rating, number of recent reviews, and

2   strength of recommendations all positively affect the demand of a book.

3   The estimates for the price equation, with log of price as dependent variable, are shown

4   in the second column in Table 4. The competitor's price in the previous period positively

5   correlates with Amazon.com's current price, which is consistent with the nature of the

6   market. The coefficient of log *rank* suggests that the higher the demand of a book, the

7   lower the price Amazon.com tends to set. This might be explained by the nature of the

8   market and competition as well. The intensity of competition across retailers for books

9   that are in high demand could prompt Amazon.com to lower its price to compete with

10  other sellers. When the demand abates, Amazon.com might feel less competitive pressure,

11  therefore making more room for higher prices. In addition, it is a common marketing

12  practice to use a popular item as "loss leader" to aggressively attract customers to the

13  store and recover the loss by selling other profitable items to the same customer.

14  The positive coefficients for recommendations, along with those for reviews and rating,

15  provide very interesting insights. As mentioned earlier, these value-added services could

16  be considered as add-on components bundled with the product itself. They are meant to

17  provide signals of quality and fit to customers. The more recommendations a book

18  receives, the more confident would the customer be about its potential fit, therefore the

19  more likely that the retailer could recover the cost of providing recommendations by

20  passing it on to the customer. Similarly, the more reviews and the higher rating a book

21  receives, the more quality information is bundled with the book; hence the more likely

22  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 with strength of recommendations as the dependent

variable, the coefficient of log *rank* in the third column in Table 4 strongly confirms the

reinforcing affect 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 collaborative filtering algorithm, which would increase

strength of the recommendations received by the base item.

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 as shown in Table 7 are very consistent

with those in Table 6 in terms of both direction and magnitude.

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. Tables 5 and 6

report the results with this simpler measure. A comparison of these results with Tables 3

and 4 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 4 should translate to -0.033 in Table 6, while the actual coefficient value in Table 6 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 impact.

### Effect of Unrelated Paired Recommendations

As mentioned in Section 3, most paired recommendations are the top books from the related recommendation list. According to Amazon, the items listed as related recommendations have the highest scores of relatedness calculated according to its proprietary algorithm. Furthermore, the item on top of the related recommendation list is automatically listed as the paired recommendation. However, a small number of paired recommendations are not top related recommendations. They are not even within the list of related recommendations at all. We refer to these recommendations as unrelated paired recommendations. Some correspondence with Amazon leads us to believe that these unrelated paired recommendations are not based on the actual purchases but are being used to promote certain authors and/or books on a paid basis.

This observation raises an interesting question: do unrelated paired recommendations that are not based on actual purchases have the same effect on sales as those paired recommendations that are based on actual sales? One argument could be that sophisticated shoppers would realize that unrelated paired recommendations do not reflect the true quality and product fit, and therefore would ignore them. An alternative

argument could be that, since Amazon usually provides an extra discount for bundles involving unrelated paired recommendations, they might prove to be more desirable to shoppers compared to items recommended through regular paired recommendations.

Given no theoretical expectations for whether there would be any difference in the impact of unrelated and regular paired recommendations, and, if any, which would be stronger, we empirically analyzed it by incorporating a dummy variable into the demand equation. The value of the dummy variable is set to one if a book is recommended through at least one unrelated paired recommendation and zero otherwise. We estimated the system of simultaneous equations again with the dummy variable but did not find any additional significant impact for unrelated paired recommendation. The coefficient for the dummy variable is insignificant while all other coefficients are virtually unchanged. We attribute this lack of effect to several possible reasons. First, the number of incidences of unrelated paired recommendations is very small, counting for only 4% of the sample. The lack of effect might be simply due to the lack of incidence. Second, since the impact of overall recommendations is very strong, the additional impact of unrelated paired recommendations, if any, could have been dominated and appear insignificant. Third, it could be the case that most shoppers do not discern the difference between related and unrelated paired recommendations and thus treat them as the same. We will elaborate more on this matter in the next section.

# 6. DISCUSSION

In this research, we build a simultaneous equation model to study the interaction among sales, recommendations, and retail prices. Our main focus is on the impact of

1 recommendations on sales. We also explore the reinforcing effect of sales on

2 recommendations. Furthermore, we examine the impact of providing various value-added

3 customer feedback services, such as recommendations and reviews, on retailer pricing

4 decisions. Compared to other studies on the same topic, our model introduces

5 simultaneity among demand, price, and strength of recommendations, and therefore

6 avoids potential bias in the inference. For example, compare the estimates from the single

7 equation model (column 4 in table 3) and those from the system of equations (table 4),

8 one can see that the true direct impact of reviews and ratings on demand are

9 underestimated in the single equation model. The cause of the underestimation is the

10 confounding of the direct impact on demand with the indirect impact, which is in the

11 opposite direction, mediated through price. Similarly, the direct impact of strength of

12 recommendations is overestimated if the indirect and negative impact of the same

13 through price is not explicitly modeled. Therefore, our empirical model provides more

14 accurate estimation of the true impact of various customer feedback mechanisms on

15 consumer demand.

16 In addition, a richer model like ours can provide more insights into the interactions

17 among demand, price, and strength of recommendations. These insights can help

18 managers make better decisions regarding the marketing mix. Our empirical results show

19 that providing value added services, such as digital word of mouth and recommendations,

20 allows retailers to charge higher prices, while at the same time increasing demand by

21 providing more information regarding the quality and match of products. This provides

guidance to management in deciding 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 impact on sales.

We also compare the difference in the impact 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%. By similar calculation, it can be seen that, on average, one extra customer review would improve the sales rank by 1%. Even though it would require different level of effort to get one more recommender or to get one more review, therefore 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. Firstly, ratings and reviews usually come from consumers having

heterogeneous shopping patterns, while recommendations are based on the purchases of consumers with homogeneous shopping patterns. Secondly, retailers usually use an objective approach based on automated algorithms to derive recommendations and hence they do not suffer from the possibility of dishonest feedbacks by phantom consumers. Thirdly, recommendations are more useful to reduce shopper's search cost for fit when facing a large variety of products. Reviews and ratings are useful when a shopper knows what she wants, but recommendations increase sales by cross-selling and suggesting items of which a shopper is unaware. All 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 in manipulating recommendations to fulfill their economic objectives. For example, Walmart.com admitted human intervention in their lists of related recommendations, and Amazon.com, in some instances, manipulates paired recommendations. By and large these interventions and manipulations are obscured from the consumers, and our analysis does not find any extra significant impact that can be attributed to those irregular recommendations. However, 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.

On the other hand, the non-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 shopper's

1   perception, as long as they keep such incidences at a minimal level. Furthermore, retailers

2   might consider a dynamic pricing mechanism for promotions based on the popularity of

3   the recommendation spot. Our empirical results on the impact of recommendations on

4   sales could provide a good starting point in designing such a pricing scheme[3].

5   Although our study provides useful insights, its limitations suggest interesting

6   opportunities for future research. First, our empirical analysis only studies the

7   recommendations of Amazon.com. Some retailers adopt different types of

8   recommendation approaches and it will be worthwhile to analyze and compare the effect

9   of various types of recommendations. On the other hand, Amazon.com is the pioneer in

10  development and implementation of recommendations and many retailers follow

11  Amazon.com's recommendation methods. Second, our analyses are limited to experience

12  goods such as books. Recommendations may not be as influential in other product

13  categories such as consumer electronics where descriptive and detailed reviews may have

14  more persuasive power than recommendations. It will be interesting to see how

15  recommendations affect sales of other product categories. Third, for some analyses, even

16  though Amazon.com's ranking methodology is changed, we have mapped sales ranks to

17  sales based on parameters derived in studies conducted before the change took place.

18  Because of this, our analysis might not provide the exact impact of recommendations on

19  sales. However, the Pareto relationship between sales rank and sales should remain true

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[3] Currently, Amazon charges a flat fee for placing a book at any recommendation spot.

even after the change in the ranking method and 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 impact of

recommenders for various products.

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1    **Table 1: Correlations between Factor Measures**

| Measures | paired recommenders (No.) | paired recommenders (Sales) | Related recommenders (No.) | Related recommenders (Sales) |
|---|---|---|---|---|
| **paired recommenders (No.)** | | | | |
| **paired recommenders (Sales)** | 0.56 | | | |
| **Related recommenders (No.)** | 0.90 | 0.52 | | |
| **Related recommenders (Sales)** | 0.59 | 0.92 | 0.67 | |

2

1 **Table 2: Definition and Descriptive Statistics**

| Data item | Definition | Mean | Median | Min | Max | Std Dev |
|---|---|---|---|---|---|---|
| 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 |
| Rank | Sales rank at Amazon.com | 1,313 | 585 | 1 | 9,990 | 1,833 |
| # 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 | 142.0 | 49.5 | 9.7 | 2,993.8 | 360.4 |
| # 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 | 337.0 | 84.0 | 9.7 | 7,219.4 | 940.9 |
| Competitor price | Selling price at Barnesandnoble.com | 16.81 | 14.95 | 5.99 | 108 | 10.56 |

2 Number of observations: 156 books x 52 days = 8,112

**Table 3: Pooled OLS Regression of Single Equation**

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

*** $p < .001$  ** $p < .01$  * $p < .05$  Standard errors are in parentheses.

1 **Table 4: 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 *price* $_{t-1}$ | - | 0.14*** (0.01) | - |
| recommendation $_{t-1}$ | - | - | 0.63*** (0.009) |
| N | 7,848 | | |
| Adjusted $R^2$ | 0.387 | | |

2  *** $p < .001$  ** $p < .01$  * $p < .05$  Standard errors are in parentheses.

1    **Table 5: Pooled OLS Regression of Single Equation (with number of recommendations)**

| Independent Variables | Dependent Variable: log *rank* | | | |
|---|---|---|---|---|
| | (1) Baseline model | (2) Recommendation added | (3) Recommendation and lagged dependent var. added | (4) Recommendation, lagged dependent var., and book effect added |
| Intercept | 8.124*** (0.186) | 7.83* (0.17) | 0.34*** (0.06) | All significant |
| log *price* | -0.088* (0.042) | -0.11** (0.04) | 0.01 (0.01) | 0.49*** (0.09) |
| Rating | 0.246*** (0.034) | 0.16*** (0.03) | 0.01 (0.010) | -0.04 (0.04) |
| Review | -0.567*** (0.01) | -0.38*** (0.009) | -0.02*** (0.003) | -0.007*** (0.001) |
| No. of Recommendations | | -0.14*** (0.003) | -0.006*** (0.001) | -0.01*** (0.002) |
| Log*rank*$_{t-1}$ | | | 0.95*** (0.003) | 0.66*** (0.008) |
| N | 7,848 | 7,848 | 7,848 | 7,848 |
| Adjusted R$^2$ | 0.30 | 0.45 | 0.95 | 0.96 |

2          *** $p < .001$  ** $p < .01$  * $p < .05$  Standard errors are in parentheses.
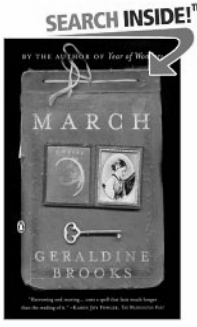
1 **Table 6: 3SLS Regression of system of equations (with number of recommendations)**

| Independent Variables | Dependent Variable | | |
|---|---|---|---|
| | log *rank* | log *price* | Recommendation |
| log *price* | 4.00*** (0.74) | - | - |
| Rating | -0.11*** (0.03) | 0.01** (0.004) | - |
| Review | -0.01*** (0.001) | 0.0008*** (0.0002) | - |
| No. of Recommendations | -0.01** (0.005) | 0.002** (0.0005) | - |
| Log$rank_{t-1}$ | 0.63*** (0.01) | - | - |
| Log *rank* | - | 0.01*** (0.002) | -0.21*** (0.05) |
| Log *price* $_{t-1}$ | - | 0.14*** (0.01) | - |
| No. of Recommendations $_{t-1}$ | - | - | 0.50*** (0.009) |
| N | 7,848 | | |
| Adjusted $R^2$ | 0.29 | | |

1 **Table 7: 3SLS Regression of system of equations (with Sales Quantity instead of Rank)**

| Independent Variables | Dependent Variable | | |
|---|---|---|---|
| | log*SalesQuantity* | log *price* | Recommendation |
| log *price* | -3.64*** (0.65) | - | - |
| Rating | 0.11*** (0.04) | 0.02** (0.004) | - |
| Review | 0.008*** (0.001) | 0.0008*** (0.0002) | - |
| Recommendation | 0.12*** (0.02) | 0.008*** (0.002) | - |
| LogSalesQuantity$_{t-1}$ | 0.60*** (0.01) | - | - |
| Log*SalesQuantity* | - | -0.02*** (0.002) | 0.12*** (0.01) |
| Log *price* $_{t-1}$ | - | 0.14*** (0.01) | - |
| recommendation $_{t-1}$ | - | - | 0.63*** (0.009) |
| N | 7,848 | | |
| Adjusted R$^2$ | 0.387 | | |

2     \*\*\* $p < .001$  \*\* $p < .01$  \* $p < .05$  Standard errors are in parentheses.

**Figure 1: Screenshot of a book webpage on Amazon.com**

RCMD: strength of recommendations

**Figure 2: Empirical model**