

December 2006

The Influence of Online Consumer Reviews on the Demand for Experience Goods: The Case of Video Games

Feng Zhu
Harvard Business School

Xiaoquan Zhang
HKUST and MIT Center for Digital Business

Follow this and additional works at: <http://aisel.aisnet.org/icis2006>

Recommended Citation

Zhu, Feng and Zhang, Xiaoquan, "The Influence of Online Consumer Reviews on the Demand for Experience Goods: The Case of Video Games" (2006). *ICIS 2006 Proceedings*. 25.
<http://aisel.aisnet.org/icis2006/25>

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICIS 2006 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

THE INFLUENCE OF ONLINE CONSUMER REVIEWS ON THE DEMAND FOR EXPERIENCE GOODS: THE CASE OF VIDEO GAMES

Economics and Information Systems

Feng Zhu

Harvard Business School
Boston, MA
feng@hbs.edu

Xiaoquan (Michael) Zhang

HKUST and
MIT Center for Digital Business
Hong Kong
zhang@ust.hk

Abstract

We examine the effect of online consumer reviews on the sales of video games. An inherent problem in measuring the influence of reviews on demand is that products receiving good reviews tend to be of high quality, and it is difficult to determine whether the review or the quality is responsible for the high demand. To circumvent this problem, we consider video games that are developed for both PlayStation 2 and Xbox and take a differences-in-differences approach to a structural model of game demand. Our results indicate that online consumer reviews have a significant influence on the sales of the video games. On average, one point increase in the average rating is associated with 4% increase in game sales. Negative ratings have a larger impact than positive ratings. In addition, we find that online reviews are more influential for less popular games. These results suggest the importance of managing online word of mouth for firms, especially for their less popular products.

Keywords: Online consumer review; word of mouth; online forum; Internet marketing

Introduction

Word of mouth (WOM) has long been recognized as an important driver of consumer demand for experience goods (goods for which the quality is uncertain prior to consumption) (Katz and Lazarsfeld 1955, Nelson 1970). Earlier studies on WOM have examined personal influence on consumers' adoption behavior (e.g. Katz and Lazarsfeld 1955, Coleman et al. 1966), as well as the linkage between professional reviews and the demand for the products (Litman 1983, Litman and Kohl 1989, Sochay 1994). Sometimes the influence of WOM could be so large that consumers may choose to optimally ignore their private signals and rely entirely on the information from others (e.g. Benerjee 1992, 1993; Ellison and Fudenberg 1995). However, conventional WOM communication is only effective within limited geographic boundaries or time span.

With the growing popularity of the Internet, the Internet has become an important source for consumers to obtain product information and user feedback. Studies have shown that Internet technologies, such as search engines or shopbots, could significantly reduce search costs (e.g. Bakos 1997; Brynjolfsson and Smith 2000). Online review systems complement these technologies as consumers could use feedback from other users to discover product quality and the fit between the product and their tastes. As a result, online reviews are particularly useful for experience goods. A report by Forrester Research shows that approximately 50% of young Internet surfers rely on WOM recommendations to purchase experience goods such as CDs, movies, videos or DVDs, and games (Godes and Mayzlin 2004; Walsh 2000).

Online reviews differ from conventional communication in several aspects. First, online reviews or discussions are recorded on various Web sites and can be easily retrieved by consumers or researchers in a later date. The ability to

trace the dates of incidences of WOM makes it easy to study WOM in a dynamic setting (Godes and Mayzlin 2004; Dellarocas et al. 2005; Chevalier and Mayzlin forthcoming). Second, unlike professional reviews, online reviews are often submitted by individual consumers. Thus, they should be more useful in examining “popular appeal” instead of “professional judgment” (Holbrook 1999). A survey by BizRate.com suggests that more than 50% of respondents consider consumer-generated reviews more valuable than expert reviews (Piller 1999). Finally, the Internet offers great efficiency and flexibility — anyone can potentially share her experience with millions of Internet users and influence their decisions through online WOM regardless of geographic boundaries.

As a result, one would expect that with the proliferation of online review systems, online reviews could be a good proxy for overall WOM and may significantly influence the demand for experience goods. The effectiveness of online reviews, however, could be very limited for a couple of reasons. First, as reviewers are not drawn from a random sample of the user population, their opinions may not reflect the preference of the general population. Anderson (1998) finds that extremely satisfied and extremely dissatisfied customers are more likely to initiate WOM transfers. Li and Hitt (2004) find potential bias in consumer reviews in early product introduction periods. Second, online forums can be manipulated by interested parties. Owners of the forums may design the Web sites to advantage their sponsors. Firms can anonymously post online reviews to praise their products or to increase the awareness of the products (Dellarocas forthcoming; Mayzlin 2006). Potential buyers may therefore heavily discount online reviews. Consequently, online reviews may not affect product sales.

The limited empirical evidence to date has provided mixed results. For instance, Chevalier and Mayzlin (forthcoming)’s study on online book reviews, Resnick and Zeckhauser (2002)’s study on eBay’s reputation profiles, and Zhang (2006)’s study on online movie reviews find that online consumer ratings have significant impact on sales. However, Chen et al. (2004)’s study on online book reviews and Duan et al. (2005)’s study on online movie reviews challenge this view and suggest only the volume of the reviews matters.

The purpose of this paper is to measure the influence of online consumer reviews on the sales of video games. An inherent problem in measuring the influence of reviews on demand is that products receiving positive reviews tend to be of high quality. Since the quality is often unobserved by researchers, it is difficult to determine whether the review or the quality is responsible for the high demand. Therefore, the positive correlations found in some of the earlier studies between reviews and product sales could be spurious. Recent studies have proposed several methods to circumvent this endogeneity problem. For example, in the context of movies, Einav (forthcoming) and Zhang (2006) use fixed effects specifications to control for unobserved movie quality. An underlying assumption of these fixed-effects specifications is that consumer tastes for the product are time-invariant and such assumption is often too strong. Godes and Mayzlin (2004) use lagged independent variables to circumvent the endogeneity issue. Their approach has to assume that the unobserved quality is not serially correlated. Elberse and Eliashberg (2003) propose a simultaneous-equations model to address the simultaneity of audience expectation and number of screens. Dubois and Nauges (2006), extending the framework proposed by Levinsohn and Petrin (2003), exploit a structural assumption about the omitted quality variable to control for the unobserved quality of wines. Other researchers have used “differences-in-differences” methods to eliminate quality signals. Reinstein and Snyder (2005) take advantage of the timing of critics’ reviews relative to a movie’s release and finds that the measured influence effect is small though still detectable. Chevalier and Mayzlin (forthcoming) examine book reviews and sales ranks on Amazon.com and BN.com at several time points to control for book-specific and book-site-specific effects.

Similar to the approach in Chevalier and Mayzlin (forthcoming), our empirical analysis hinges on the video games that are released on two different consoles: PlayStation 2 and Xbox. We apply a differences-in-differences approach to a structural model of game demand to circumvent the endogeneity problem. By taking the differences between the sales of the same game title on the two consoles, we eliminate unobserved game characteristics that may impact both reviews and sales. By examining the differences across consoles over time, we control for the taste differences between the console-installed bases that may influence both reviews and sales. Our paper contains several major differences from Chevalier and Mayzlin (2005). First, we employ a discrete choice model of demand to capture substitution among different games, whereas Chevalier and Mayzlin (forthcoming) do not consider such effects.¹ Second, Chevalier and Mayzlin (forthcoming) use ranks from two different ranking systems to approximate book sales. As ranks for books with very low sales are not disclosed at BN.com, their sample is truncated. In addition, ranks could be poor measures of sales of infrequently purchased books. We use actual sales data. Third, Chevalier

¹Possible substitution effects for books could come from other books in the same category or used books in the second-hand book market on Amazon.com.

and Mayzlin (forthcoming) look at how reviews on Amazon.com and BN.com affect book sales at both Web retailers. As a result, their analysis has to control for effects across the two sites. In our case, as the two consoles are incompatible with each other and most game players only own one console, we do not have such concerns. In addition, as our analysis matches review data from a Web site that does not sell games directly to aggregate game sales, our approach is likely to be free from manipulation of the review or ranking systems by the site owner.²

We also examine the differential effects of online reviews on popular and less popular games. Online reviews substitute and complement offline WOM communication about product quality. Therefore, when quality information is readily available from other channels, we expect decreased reliance on online reviews. In the context of video games, consumer awareness of popular games is likely to be high, as these games are frequently featured in game magazines or in-store demos and discussed among friends. As a result, when making purchase decisions, consumers may not resort to online review systems for quality information, or are less influenced by online reviews. Likewise, we expect increased reliance on online reviews for less popular games. We therefore hypothesize that online reviews have a greater influence on product sales for less popular products than for popular products.

Our empirical results support the view that online WOM affects consumers' purchasing behavior. We find that the average rating of the reviews has significant influence on the sales of video games — on average, one point increase in the valence leads to 4% increase in sales. We also find that online reviews are more important for less popular games. These results also suggest that at least some aspects of online WOM are proxies for overall WOM. Given the operational advantages of measuring online WOM, firms could use online reviews to proactively manage WOM, especially for less popular products (Chen and Xie 2005).

The rest of the paper is organized as follows. In the next section, we give background information on the cross-platform development in the video game market. Then we establish the empirical model and discuss the data sources for this study. We report and discuss the results in the next section. Finally, we present the implications of our results and conclude.

Cross-platform Development in the Video Game Industry

The video game industry is an over ten billion dollar industry in the United States. Manufacturers of video game consoles face a “two-sided market”: game players value video consoles for the number of game titles they are associated with and game publishers value consoles for their installed bases (e.g. Evans (2003)).

Both sides of the market are characterized by intense inter- and intra-generation competition. Schilling (2003) provides an overview of the evolution of the video game industry. Today the most popular consoles in the market are Sony's PlayStation 2, Nintendo's GameCube, and Microsoft's Xbox 360. Sony has dominated the 128-bit console market, with the PlayStation 2 accounting for 55.6% of console installed base.³

Development is normally funded by a publisher. The average cost of developing a contemporary video game is about seven million dollars (Montagne 2006). A game can take from one to three years to develop depending on the genre, scale, development platform, and amount of assets.

In the early days, most game titles were only developed for a single console. Whenever the game was ported to a new console, a different team would have to rewrite the entire game. Assembly language, a human-readable notation for the machine language, was used to write most games at that time as it optimizes the processing speed and requires very little overhead.

Today, as processing speed is no longer a critical issue, high-level languages such as C++ become the most popular game development languages (Goodwin 2005). In addition, although libraries for different consoles are not compatible with each other, game developers can take advantage of cross-platform middleware platforms (e.g. Criterion's Renderware 3D development platform) to program a game in a single language and have the game run on several consoles. Publishers no longer see cross-platform development as an option to do later. Instead, they often mandate the developers to release games on all three major console platforms simultaneously. It is quite

²Indeed, Chevalier and Mayzlin (forthcoming) find that Amazon has been active in pruning reviews. Chen and Xie (2005) discusses firms' various strategic responses to third party product reviews.

³Source: The NPD Group as of March 2006. <http://www.us.playstation.com/PressReleases.aspx?id=338>, accessed April 2006.

common today to see an advertisement for a new game with the plethora of logos at the end: “PlayStation 2, Xbox, GameCube” (Reimer 2005).

Model

Demand Model for Video Games

We estimate a nested logit demand model for games. Assume there are J games available on console k and an outside option labeled 0. We place the J games in one group, g , and the outside option in another group by itself. The perceived utility of player i from purchasing a game j , $j \in [1, J]$, at time t is a function of game characteristics (ξ_{jt}^k) , the vector of lagged review variables $(R_{j,t-1}^k)$, price (p_{jt}^k) , and unobservable parameters:

$$u_{ijt}^k = \beta_0 + \beta_1 p_{jt}^k + R_{j,t-1}^k \Gamma + \xi_{jt}^k + \zeta_{jgt}^k + (1-\sigma) v_{ijt}^k \quad (1)$$

ζ_{jgt}^k represents player utility common to all games of group g . v_{ijt}^k is an i.i.d. extreme-value distributed error term that represents player i 's idiosyncratic taste for games in group g . The parameter $\sigma \in [0, 1)$ measures the correlation of unobserved utility among games in the same group. When $\sigma \rightarrow 1$, games within a group are perfect substitutes, whereas when $\sigma = 0$ they are independent and we have the simple logit model.

We normalize the utility from the outside good to be zero. We denote the market share of game j as s_j and the market share for game j within group g as $s_{j|g}$. Following Berry (1994) and Cardell (1997), the demand equation for the nested logit model can be derived as:

$$\ln(s_{jt}) - \ln(s_{0t}) = \beta_0 + \beta_1 p_{jt}^k + R_{j,t-1}^k \Gamma + \sigma \ln(s_{j|g}) + \xi_{jt}^k \quad (2)$$

Identification

Given the panel structure of data, we decompose the unobservable component ξ_{jt}^k as

$$\xi_{jt}^k = \theta_{jt} + \eta_j^k + \varepsilon_{jt}^k$$

where θ_{jt} is a game-specific component which is the same for the same game across different platforms but can vary over time and η_j^k is the console-specific effect. The former is related to factors such as promotions by game publishers, the brands of the game publishers, and the quality of the games. The latter is to capture the difference in players' tastes of the consoles and the fit between game j and console k . Even for the same game title, players' utility may be different due to difference in console characteristics such as clock speed. Therefore, η_j^k is time invariant but may vary across games on the same console. ε_{jt}^k is an i.i.d. normal error term varying across games and over time.

We restrict our analysis to games that are developed for two console systems, Sony's PlayStation 2 and Microsoft's Xbox, for a couple of reasons. First, PlayStation 2 and Xbox were the two largest players in the console market and had the largest game libraries during the period for which we have review data. Second, both consoles target at adults between 18 and 34, positioning themselves directly against each other. Therefore, we expect the two gaming populations to be very similar to each other. Table 1 compares features of the two consoles. The only major differences between the two consoles are the clock speed and the amount of memory.

Table 1

Features of PlayStation 2 and Xbox Consoles. We compare the features of PlayStation 2 and Xbox consoles. The only major differences between the two consoles are the clock speed and the amount of memory.

	PlayStation 2	Xbox
Manufacturer	Sony	Microsoft
Launch Date in the US	October 2000	November 2001
Price on the Launch Date	\$299	\$299
CD/DVD Based	Yes	Yes
Bits	128	128
Clock Speed	300 MHZ	733 MHZ
RAM	38 MB	64 MB
Network Compatibility	Yes	Yes

Following Equation (2), using superscripts p and x to denote PlayStation 2 and Xbox respectively, we have

$$\ln(s_{jt}^p) - \ln(s_{0t}^p) = \beta_0 + \beta_1 p_{jt}^p + R_{j,t-1}^p \Gamma + \sigma \ln(s_{jt|g}^p) + \theta_{jt} + \eta_j^p + \varepsilon_{jt}^p \quad (3)$$

$$\ln(s_{jt}^x) - \ln(s_{0t}^x) = \beta_0 + \beta_1 p_{jt}^x + R_{j,t-1}^x \Gamma + \sigma \ln(s_{jt|g}^x) + \theta_{jt} + \eta_j^x + \varepsilon_{jt}^x \quad (4)$$

We use the size of installed base of each console as the potential market. The within-group market shares, $\ln(s_{jt|g}^p)$ and $\ln(s_{jt|g}^x)$, are by definition endogenous and require instrument variables. Following Einav (forthcoming), we use the number of games available for each console at time t as the instrument for the within-group market share. A large number of games implies intense competition, and therefore should be negatively associated with the within group share.

θ_{jt} contains both observed and unobserved game-specific characteristics. The unobserved characteristics are likely to be correlated with independent variables. Omitting these unobserved effects would produce biased coefficients. As θ_{jt} is the same across console systems, we eliminate the game-specific effects by differencing the data across consoles:

$$\Delta M_{j,t} = \beta_1 \Delta p_{j,t} + \Delta R_{j,t-1} \Gamma + \sigma \Delta WGS_{j,t} + \Delta \eta_j + \varepsilon_{j,t} \quad (5)$$

where $\Delta M_{j,t} = [\ln(s_{jt}^p) - \ln(s_{0t}^p)] - [\ln(s_{jt}^x) - \ln(s_{0t}^x)]$, $\Delta p_{j,t} = p_{jt}^p - p_{jt}^x$, $\Delta R_{j,t-1} = R_{j,t-1}^p - R_{j,t-1}^x$, $\Delta WGS_{j,t} = \ln(s_{jt|g}^p) - \ln(s_{jt|g}^x)$, and $\Delta \eta_j = \eta_j^p - \eta_j^x$.

$\Delta \eta_j$, which captures the differences in console-specific effects, is also unobserved but does not vary over time. As the console differences might affect differences in game prices and reviews, we take an additional difference between period t and $t + \Delta t$ and have:

$$\Delta \Delta M_{j,t} = \beta_1 (\Delta \Delta p_{j,t}) + (\Delta \Delta R_{j,t-1}) \Gamma + \sigma (\Delta \Delta WGS_{j,t}) + \varepsilon_{j,t} \quad (6)$$

Equation (6) is our empirical specification. In our analysis, we use $\Delta t = 1$ but our results are robust to the choice of Δt .

Data

Data on console sales and game sales come from the NPD Fun Group, a leading market research firm that tracks this industry. NPD collects data from approximately 17 leading U.S. retail chains that account for 80% of the U.S. market. From these data, NPD formulates estimates of sales figures for the entire U.S. market. We obtain monthly data for PlayStation 2 and Xbox and their associated games up to October 2005. For each game, we compute the average monthly price by dividing the monthly dollar value of sales by the volume of units sold.

We gather review data from GameSpot.com (also known as VideoGames.com). According to Ranking.com, GameSpot.com is the 172th most visited site among all Web domains and is the most popular one on video games.⁴ GameSpot publishes three kinds of reviews: editors' reviews, players' reviews, and reviews from other sources. Editors at GameSpot review most games on or around the day on which they ship to retail channels. In March 2003, GameSpot started to publish player reviews. To ensure the quality of these reviews, only GameSpot paid subscribers or users who have sufficient level of experience (as demonstrated by their participation in other parts of the site such as forums) could post reviews. At most one review is allowed from the same login name for a given game. These policies minimize the potential manipulation of the review system and ensure that reviews are of high quality. Reviewers also use a scale ranging from 1 to 10 for their reviews, with 10 being the best and 1 being the absolute worst, for each of the five aspects (gameplay, graphics, sound, value, and tilt). For each review, GameSpot publishes ratings for each aspect as well as their average. We use the average rating of all five aspects in our analysis. In addition, GameSpot collects critics' reviews from other sources such as Yahoo! Games and Hardcore Gamer Magazine, and publishes aggregate scores based on these reviews. Most of these reviews are published within a month after the release of the games. The reviews by the editors at GameSpot and from other sources are rarely updated after they are published, and therefore provide little variation over time. Their effects are eliminated in our differences-in-differences estimation. The player reviews, however, vary both across consoles and over time, and are the focus of our analysis.⁵ Even for the same game titles, player reviews are often different across consoles.

For each game in each month before October 2005, we collect its average rating, the coefficient of variation of the ratings, the total number of reviews, and the average length of the reviews. The average rating reflects the level of consumer satisfaction. The coefficient of variation is measured as the ratio of the standard deviation to the mean rating. It is a unitless measure of rating dispersion that allows comparison of degree of disagreement among games with different mean ratings. We also include the total number of reviews as a measure of the volume of discussions. Chen et al. (2004) find as the number of posts increases, the overall rating converges to the true quality. Therefore, from a visitor's point of view, a large number of reviews may be associated with more accurate reflection of the quality of a game. The number of reviews may also signal the popularity of the game. As games, in particular those can be played online, may exhibit direct network effects, players' willingness to purchase a game may increase with the number of players who own the same game. The review content often contains additional information. However, these data tend to be costly to collect and difficult to interpret quantitatively (Godes and Mayzlin 2004; Chevalier and Mayzlin forthcoming). Therefore, we only include a cost-effective measure, the length of reviews, measured by the total number of typed characters. These four metrics have been used in previous studies on reviews. For example, Zhang (2006) uses the average rating of the reviews and the coefficient of variation of the ratings. Cheng and Fay (2003) use the number of ratings. Chevalier and Mayzlin (forthcoming) examine the average length of the reviews.

Although GameSpot offers a convenient way to measure online WOM, its reviews may not be representative for all online opinions on specific games. Players could also obtain review information from other channels such as online bulletin boards and chat rooms. This potential sample-selection bias, however, would weaken the estimated relationship between online reviews and sales, and would strengthen our argument.

We merge the sales data with the review data to obtain the final data set.

Results

Our final data set consists of 159 game titles that are released for both PlayStation 2 and Xbox. Twenty-nine of them are released on different dates for the two consoles and are removed from the sample.⁶ Similar to other empirical studies that use discrete choice models of product differentiation (e.g. Argentesi and Filistrucchi forthcoming, Einav forthcoming, Rysman 2004), a natural concern is the assumption of single purchase — each consumer purchases at most one game in each period. This seems to be a reasonable assumption in the case of video games. According to a recent survey, more than 80% of consumers on average purchase one game or less in each month (Pidgeon and Hu 2003). Consumers' purchase frequency, however, could exhibit seasonal patterns. Figure 1 shows mean revenue and

⁴<http://www.ranking.com>, accessed April 2006. Ranking.com tracks the popularity of the top one million Web domains.

⁵We also looked at other less popular game Web sites such as IGN.com. Almost all of them only provide professional reviews.

⁶Including these 29 games does not change our results.

mean units sold by month for all games over the sampling period. As our data on monthly game sales exhibit strong holiday effects, we remove observations in November and December from our data set.

Figure 1

Mean units and mean revenue by month for all games. The sales (in volume or dollars) are significantly higher in November and December, suggesting strong holiday effect.

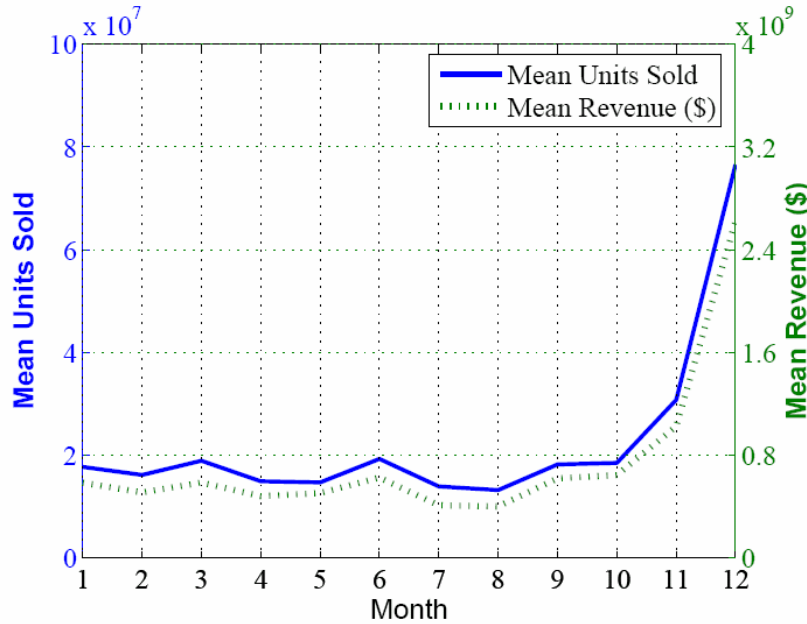


Table 2 provides summary statistics for games in our sample. A t-test indicates that both the monthly unit sales of games and the monthly average number of games on PlayStation 2 are significantly greater than those on Xbox. The result is consistent with the larger installed base of PlayStation 2 console and the strong indirect network effects documented in Clements and Ohashi (2005). The prices for games on the two consoles are at about the same level, most likely due to the intense competition among game titles on each console.

Table 2

Summary Statistics for Games. Panel A and B present summary statistics for games developed on PlayStation 2 and Xbox in our sample. The time period is from March 2003 to October 2005. The monthly price is calculated by dividing the monthly dollar value of sales by the volume of units sold.

Panel A: Summary Statistics for Games on PlayStation 2

Variable	No. of Obs.	Mean	Std. Dev.	Min	Max
Monthly Sales (Units)	1551	9653.91	18313.95	8	248967
Monthly No. of Games	27	810.63	187.23	520	1124
Monthly Price (\$)	1551	21.68	10.46	4.42	47.92

Panel B: Summary Statistics for Games on Xbox

Variable	No. of Obs.	Mean	Std. Dev.	Min	Max
Monthly Sales (Units)	1596	5508.54	10976.29	3	163162
Monthly No. of Games	27	475.78	150.66	235	725
Monthly Price (\$)	1596	21.17	10.53	2.54	47.93

Table 3

Summary Statistics for Reviews. Panel A and B present summary statistics for reviews of games on PlayStation 2 and Xbox as of October 2005 in our sample. The average rating is the arithmetic mean of all ratings from March 2003 and October 2005 for each game. The variation of ratings is measured as the ratio of the standard deviation to the mean rating. The number of reviews is the total number of posted reviews for each game. The average length of reviews is measured by the arithmetic mean of total number of typed characters in all reviews for each game.

Panel A: Summary Statistics for Reviews of PlayStation 2 Games					
Variable	No. of Obs.	Mean	Std. Dev.	Min	Max
Average Rating	130	7.55	1.50	2.18	9.55
Variation of Ratings	130	0.14	0.12	0	0.53
No. of Reviews	130	10.87	12.85	1	63
Average Length of Reviews	130	2108.24	941.77	585	5091.75

Panel B: Summary Statistics for Reviews of Xbox Games					
Variable	No. of Obs.	Mean	Std. Dev.	Min	Max
Average Rating	130	7.54	1.40	1.35	9.40
Variation of Ratings	130	0.16	0.16	0	0.73
No. of Reviews	130	12.58	17.83	1	104
Average Length of Reviews	130	2018.03	912.69	540	5508.00

Table 3 presents the summary statistics of reviews as of October 2005. The data suggest that reviews are overwhelmingly positive for games on both consoles. Similar patterns have been observed in other context such as book reviews at Amazon (Chevalier and Mayzlin forthcoming) and reputation profiles at eBay (Resnick and Zeckhauser 2002). On average, we have more than ten reviews for each game. However, the distribution of the number of reviews is skewed. The number of reviews ranges from 1 to 63 for games on PlayStation 2 and from 1 to 104 for those on Xbox. The minimum length of these reviews is 540, indicating that each review has been carefully written. We find no significant difference in any of the four metrics between the two consoles, suggesting that the two gaming populations are quite similar.⁷

Figure 2 shows the mean prices, units sold, and ratings for games on PlayStation 2 and Xbox respectively. In all three figures, the patterns for PlayStation 2 and for Xbox are quite similar. Both average price and average units sold are declining over time. The average price declines almost linearly during the first 10 months, and the average units sold drops significantly for the first few months.⁸ Average ratings in the first couple of months are significantly higher than those in later months. This pattern suggests the existence of self-selection bias in the reviews, and is similar to that reported in Dellarocas et al. (2005) and Li and Hitt (2004). One possible explanation is that hard-core aficionados tend to buy the games immediately after they are released, and these aficionados tend to like the games more than other gamers. The variance of the mean ratings increases over time as we have fewer reviews for old games.⁹

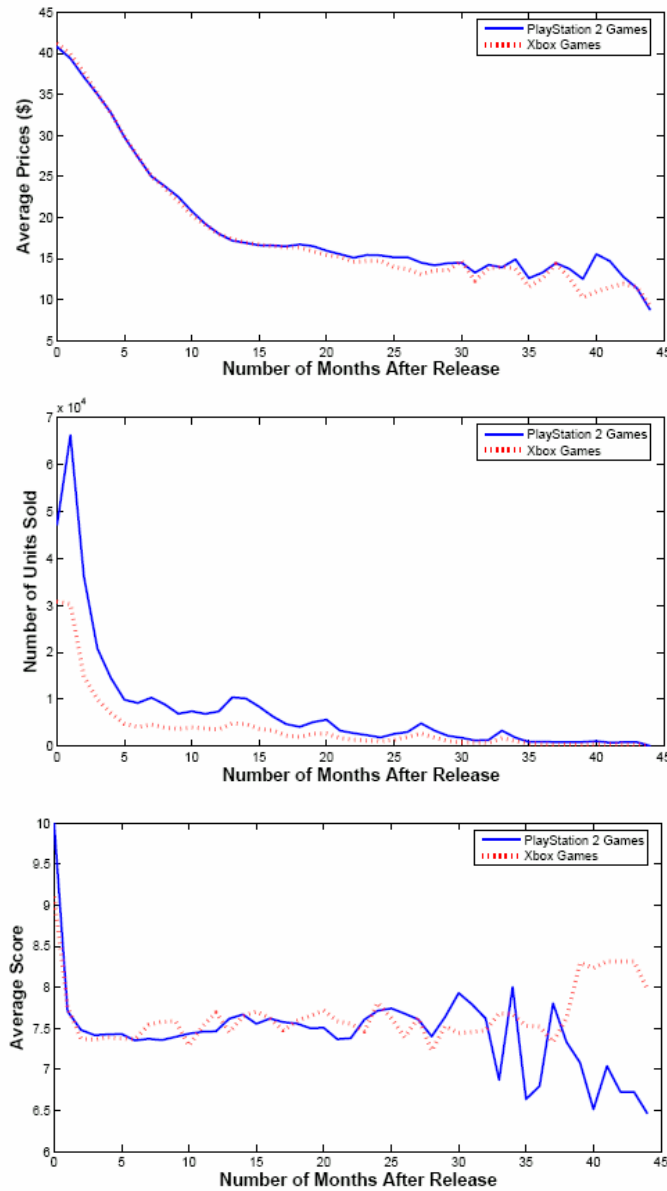
⁷One concern is that the same reviews may be posted for both consoles and as a result, reviews from the two gaming populations are artificially very similar. We check this possibility and find that only 3.3% of the reviews are posted for both consoles.

⁸As many games are not released during the first days in the month, mean units sold during the first month of the release for games on both consoles appear relatively low.

⁹The average life cycle of all games is about 33 months.

Figure 2

Mean prices, units sold and ratings over time for games on PlayStation 2 and Xbox. X-axis is the number of months after the release of the games. As many games are not released during the first days in the month, mean units sold during the first month of the release for games on both consoles appear relatively low.



We now proceed to test the influence of consumer reviews on game demand. Table 4 presents the regression results based on the differences-in-differences specification. We use the differences of $\ln(s_{jt}) - \ln(s_{0t})$ across consoles and over time as the dependent variables in all models. In Model I, we use the differences-in-differences measures of price, average rating of the reviews and within group share of the games. In Model II, we add other review variables such as the differences-in-differences measures of the variation of the ratings, the number of reviews, and the

average length of the reviews. We take the natural logarithm of these independent variables¹⁰. The results indicate that higher prices decrease sales while greater average ratings improve sales. Model III and IV focus on different ways of measuring review valence. We replace the average rating of the reviews with the fractions of ratings that are above 9 (“superb” based on GameSpot interpretation) and below 4 (“bad”). While the coefficients for the fraction of “superb” ratings are positive, they are not significant. The coefficients for the fraction of “bad” ratings are significantly negative. In addition, they are greater in absolute value than those for the “superb” ratings, indicating that negative ratings carry more weight.

Table 4

Differences-in-Differences Estimation for Measuring the Influence of Reviews on Game Demand. We use Equation (6) as the regression model. The dependent variable is $\Delta\Delta(\ln(s_{jt}) - \ln(s_{0t}))$. $\Delta\Delta$ indicates that we take the differences of the variable across console and over time. All regressions employ an ordinary least square specification. We use the total number of games for each console in each month as the instrument for within group share. Heteroscedasticity-adjusted standard errors in brackets.

Model	I	II	III	IV
$\Delta\Delta$ Price	-1.32*** [0.08]	-1.32*** [0.08]	-1.32*** [0.08]	-1.31*** [0.08]
$\Delta\Delta$ Average Rating	0.25** [0.11]	0.23** [0.10]		
$\Delta\Delta$ % of “Superb” Ratings			0.24 [0.24]	0.30 [0.24]
$\Delta\Delta$ % of “Bad” Ratings			-0.43*** [0.14]	-0.42** [0.18]
$\Delta\Delta$ Within Group Share	0.26*** [0.08]	0.26*** [0.08]	0.27*** [0.08]	0.26*** [0.08]
$\Delta\Delta$ Variation of Rating		-0.1 [0.13]		-0.16 [0.16]
$\Delta\Delta$ Number of Reviews		0.11* [0.06]		0.13** [0.06]
$\Delta\Delta$ Length of Review		-0.02 [0.06]		-0.01 [0.06]
Observations	1276	1276	1276	1276
R-squared	0.41	0.41	0.41	0.41

* significant at 10%; ** significant at 5%; *** significant at 1%

We also find that the number of reviews has positive effects, albeit at a lower significance level. One possible explanation is that a large number of reviews signal the popularity of the game, and because of direct network effects, players are more likely to purchase games owned by many others. In addition, the length of the reviews does not affect sales. Its coefficients are negative and insignificant in all models. This suggests that reviewers may use longer explanations to express “mixed” opinions. Panel A in Table 5 suggests that as the ratings get higher, the average length of reviews is generally increasing. But for the dominating range (ratings in the high range between 8 and 10), the average length of reviews is actually shorter than that of ratings between 6 and 8. Regression results in Panel B support this observation. Regressing the length of reviews on the rating, we have three simple models. Model I takes the rating as the only independent variable, and the parameter estimate is not significant. Model II adds the square of the rating as another independent variable to account for possible curvilinear relationship, and both variables are significant, suggesting that longer reviews are used for mixed opinions. Model III adds to the previous model a dummy variable for PlayStation 2 games. The insignificant parameter estimate suggests that the result is robust across the consoles, and it gives support that the reviewers on the two platforms are very similar. A simple calculation reveals that games with ratings around 6.9 tend to receive the longest reviews.

¹⁰We use the logarithms of (the number of reviews + 1), (the average length of the reviews + 1) and (the standard deviation + 1) to handle zero reviews and ratings with no variation.

Table 5

Examining the Relationship between Lengths of Reviews and Ratings. Panel A summarizes the average length of reviews for different ranges of ratings. The average length of reviews is the longest for ratings between 6 and 8. Panel B confirms this curvilinear relationship in a regression framework. The dependent variable is the length of review. All regressions employ an ordinary least square specification. Heteroscedasticity-adjusted standard errors in brackets.

Range of Ratings	Average Length of Reviews	No. of Obs.	Std. Dev.
$0 \leq \text{rating} \leq 2$	1626.5	40	698.4
$2 < \text{rating} \leq 4$	1962.0	100	978.8
$4 < \text{rating} \leq 6$	2241.1	271	1307.5
$6 < \text{rating} \leq 8$	2615.7	978	1684.6
$8 < \text{rating} \leq 10$	2380.6	2428	1550.9

Model	I	II	III
Rating	10.8 [12.58]	673.50*** [63.22]	673.85*** [63.28]
Rating ²		-49.06*** [4.85]	-49.09*** [4.86]
Dummy for PlayStation 2 Games			26.36 [50.23]
Observations	3817	3817	3817
R-squared	0.00	0.02	0.02

* significant at 10%; ** significant at 5%; *** significant at 1%

From the regression results in Table 5, we can also compute the demand elasticities with respect to prices and ratings. We include the detailed derivation for computing the elasticities in the appendix. We find that on average, the price elasticity is -1.8 and the rating elasticity is 0.31 (based on Model II). In addition, on average one dollar increase in price leads to 7 percent drop in game sales, and one point increase in average rating leads to 4 percent increase in game sales.

We now examine the differential effects of reviews on popular and less popular games. For each game, we first compute its average monthly sales in the first three months after its release. We then calculate the mean of these average monthly sales of all games. We consider games whose average performance in the first three months is above the mean performance as popular games and the rest of the games as less popular ones. Games that are released in the last two months of our data set (i.e., September 2005 and October 2005) are thus dropped from the analysis. We choose the first three months' sales as the indicator for game popularity as the first three months' sales typically account for more than 40% total sales for a game title. In addition, this choice allows us to use most of the data in our sample. Other time windows such as half year provide very similar results. We repeat our regression analysis for each group and report the results in Table 6.

We find that for popular games, the coefficients on the rating variables, albeit having the right signs, are insignificant. For less popular games, the coefficients of the rating variables are greater in absolute value than those reported in Table 4. The coefficients of average rating and fraction of "bad" ratings are statistically significant. These results suggest that online reviews are more influential for less popular products. The significance of the number of reviews disappears for less popular games, most likely due to the fact that most of these games do not have network capability and thus exhibit little direct network effects.

Table 6

Examining the Differential Effects of Reviews on Popular and Less Popular Games. We partition the games into two groups, popular games and less popular games, based on the first three months sales. Games that are released in the last two months of our data set (i.e., September 2005 and October 2005) are dropped from the analysis. We repeat analysis in Table 4 for each group. All regressions employ an ordinary least square specification. We use the total number of games for each console in each month as the instrument for within group share. Heteroscedasticity-adjusted standard errors in brackets.

Model	I	II	III	IV	V	VI	VII	VIII
Game Type		Popular Games				Less Popular Games		
$\Delta\Delta$ Price	-1.41*** [0.13]	-1.41*** [0.14]	-1.41*** [0.13]	-1.41*** [0.14]	-1.27*** [0.09]	-1.27*** [0.09]	-1.26*** [0.09]	-1.26*** [0.09]
$\Delta\Delta$ Average Rating	0.23 [0.14]	0.21 [0.13]			0.27* [0.15]	0.31* [0.18]		
$\Delta\Delta$ % of "Superb" Ratings			0.10 [0.15]	0.18 [0.12]			0.36 [0.41]	0.40 [0.43]
$\Delta\Delta$ % of "Bad" Ratings			-0.17 [0.18]	-0.00 [0.25]			-0.51*** [0.17]	-0.62*** [0.25]
$\Delta\Delta$ Within Group Share	0.15 [0.15]	0.13 [0.15]	0.15 [0.15]	0.13 [0.15]	0.31*** [0.10]	0.31*** [0.10]	0.32*** [0.10]	0.32*** [0.10]
$\Delta\Delta$ Variation of Rating		-0.08 [0.20]		-0.17 [0.22]		-0.19 [0.20]		-0.28 [0.23]
$\Delta\Delta$ Number of Reviews		0.14* [0.08]		0.15* [0.08]		0.11 [0.11]		0.14 [0.10]
$\Delta\Delta$ Length of Review		0.03 [0.07]		0.04 [0.07]		-0.10 [0.11]		-0.07 [0.10]
Observations	647	647	647	647	628	628	628	628
R-squared	0.40	0.41	0.40	0.41	0.42	0.42	0.42	0.42

* significant at 10%; ** significant at 5%; *** significant at 1%

Conclusions

The Internet has fostered an explosion of new ways for people to communicate with each other, and online discussion forums allowed people to exchange ideas with total strangers. These new ways of communication pose both challenges and opportunities to the firms. On one hand, it is intimidating to manage the reputation profile generated from the WOM process of thousands of people who are complete strangers to each other. On the other hand, the Internet provides the companies with a way to record, retrieve, and measure the reputation profiles.

Understanding how consumers react to online reviews is of vital importance to firms who rely on WOM to disseminate information about their products. This paper has examined, in the context of video games, the impact of online consumer reviews on sales. We find that for the games in our sample, the consumer reviews influence the product sales, even after eliminating the unobservable game-specific characteristics and controlling for possible heterogeneities in consumer tastes across the console platforms. Specifically, we estimate that a one-point increase in a game's online average rating on average leads to a 4% increase in its sales in the following month. These findings are consistent with the survey results reported in Bounie (2005) that as most gamers are young and have limited income, they frequently use online reviews to avoid bad purchases. We also find that for less popular games, the estimated impact of online ratings is even higher, suggesting WOM playing a bigger role for less popular games.

These results suggest that online reviews complement offline WOM. It is therefore important for firms to design effective online marketing strategies, especially for their less popular products. For example, firms could use promotional chats or invite users to review their products to increase the awareness of their products.

There are several directions in extending this work. First, if online reviews provide useful information for firms and consumers, how could we elicit more user contribution? It is not yet clear what motivates the reviewers to write these reviews. Most of the potential payoffs discussed in the case of open source communities (e.g. user need for particular software and career advancement (Lerner and Tirole 2002; Lerner and Tirole 2005; Von Hippel 2001)) are either weak or not applicable here.

Second, future research could look into the differences between online and offline WOM. One eminent difference is that online reviews can be more easily manipulated, as sources of these online reviews are usually anonymous (Dellarocas forthcoming).¹¹ If the market for online reviews is efficient, then any inflation or deflation in product reputation should be adjusted by the consumers quickly such that in the long run, there are no gains to distorting the reviews. Although our paper finds evidence that there maybe financial reasons for the firms to bias the reviews, it is not necessary that firms manipulating reviews can obtain advantages in the long run, as consumers' reaction to inflated reviews may negatively affect the firms' profitability. It is thus interesting to examine how this interaction plays out over time.

Third, future research could compare the influence of online reviews among multiple products. We believe that the strength of the influence is correlated with the size of user population being online.

Finally, product-level marketing data may help us study the best practices of managing online WOM.

Acknowledgements

We thank Marco Iansiti and the NPD Group for access to the data used in the research. We also thank anonymous reviewers of the 2006 International Conference on Information Systems for many insightful comments. The authors made equal contributions.

References

- Anderson, E. W. 1998. Customer satisfaction and word of mouth. *Journal of Service Research* **1**(1) 5–17.
- Argentesi, E., and L. Filistrucchi, forthcoming, "Estimating market power in a two-sided market: the case of newspapers," *Journal of Applied Econometrics*.

¹¹Indeed, a New York Times story revealed that some prominent authors had apparently pseudonymously written themselves five-star reviews (Harmon 2004).

- Bakos, Y. J. 1997. Reducing buyer search costs: Implications for electronic marketplaces. *Management Science* **43**(12) 797–817.
- Banerjee, A. V. 1992. A simple model of herd behavior. *Quarterly Journal of Economics* **107**(3) 797–817.
- Banerjee, A. V. 1993. The economics of rumors. *Review of Economic Studies* **60**(2) 309–27.
- Berry, S., 1994, “Estimating Discrete-Choice Models of Product Differentiation,” *RAND Journal of Economics*, **25**, 242–262.
- Bounie, D., M. Bourreau, M. Gensollen, and P. Waelbroeck, 2005, “Do Online Customer Reviews Matter? Evidence from the Video Game Industry,” mimeo.
- Brynjolfsson, E., M. Smith. 2000. Frictionless commerce? A comparison of internet and conventional retailers. *Management Science* **46**(4) 563–585.
- Cardell, S. N., 1997, “Variance Components Structures for the Extreme-Value and Logistic Distributions with Application to Models of Heterogeneity,” *Econometric Theory*, **13**(2), 185–213.
- Chen, P. S., S. Wu, J. Yoon. 2004. The impact of online recommendations and consumer feedback on sales. *Proceedings of the International Conference on Information Systems, ICIS 2004*. 711–724.
- Chen, Y., S. Fay, and Q. Wang, 2003, “Marketing Implications of Online Consumer Product Reviews,” mimeo.
- Chen, Y., J. Xie. 2005. Third-party product review and firm marketing strategy. *Marketing Science* **24** 218–240.
- Chevalier, J. A., and D. Mayzlin, forthcoming, “The Effect of Word of Mouth on Sales: Online Book Reviews,” *Journal of Marketing Research*.
- Clements, M. T., and H. Ohashi, 2005, “Indirect Network Effects and the Product Cycle: Video Games in the U.S., 1994-2002,” *Journal of Industrial Economics*, **LIII**(4), 515–542.
- Coleman, J. S., E. Katz, and H. Menzel, 1966, *Medical Innovation: A Diffusion Study*. Indianapolis: Bobbs-Merrill Co.
- Dellarocas, C., forthcoming, “Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms,” *Management Science*.
- Dellarocas, C., N. Awad, and X. M. Zhang, 2005, “Using online ratings as a proxy of word-of-mouth in motion picture revenue forecasting,” mimeo.
- Duan, W., B. Gu, A. B. Whinston. 2005. Do online reviews matter?—An empirical investigation of panel data. Working Paper, University of Texas at Austin.
- Dubois, P., and C. Nauges, 2006, “Identifying the effect of unobserved quality and experts’ reviews in the pricing of experience goods: Empirical application on Bordeaux wine,” mimeo.
- Einav, L., forthcoming, “Seasonality in the U.S. motion picture industry,” *RAND Journal of Economics*.
- Elberse, A., and J. Eliashberg, 2003, “Demand and supply dynamics for sequentially released products in international markets: The case of motion pictures,” *Marketing Science*, **22**(3), 329–354.
- Ellison, G., and D. Fudenberg, 1995, “Word of Mouth Communication and Social Learning,” *Quarterly Journal of Economics*, **110**, 612–643.
- Evans, D. S., 2003, “Some Empirical Aspects of Multi-Sided Platform Industries,” *Review of Network Economics*, **2**(3), 191–209.
- Godes, D., and D. Mayzlin, 2004, “Using online conversations to study word-of-mouth communication,” *Marketing Science*, **23**(4), 545–560.
- Goodwin, S., 2005, *Cross-Platform Game Programming*. Charles River Media.
- Harmon, A. 2004. Amazon glitch unmasks war of reviewers. *New York Times* February 14.
- Holbrook, M. B., 1999, “Popular Appeal versus Expert Judgments of Motion Pictures,” *Journal of Consumer Research*, **26**(2), 144–155.
- Katz, E., and P. Lazarsfeld, 1955, *Personal Influence*. Glencoe, Free Press.
- Lerner, J., J. Tirole. 2002. Some simple economics of open source. *Journal of Industrial Economics* **50**(2) 197–234.
- Lerner, J., and J. Tirole, 2005, “The economics of technology sharing: Open source and beyond,” *Journal of Economic Perspectives*, **19**(2), 99–120.
- Levinsohn, J., and A. Petrin, 2003, “Estimating production functions using inputs to control for unobservables,” *Review of Economic Studies*, **70**(243), 317–341.
- Li, Xinxin, Lorin M. Hitt. 2004. Self selection and information role of online product reviews. Working Paper, Wharton School.
- Litman, B., and L. Kohl, 1989, “Predicting financial success of motion pictures: The 80’s experience,” *Journal of Media Economics*, **2**, 35–50.
- Litman, B. R., 1983, “Predicting the success of theatrical movies: An empirical study,” *Journal of Popular Culture*, **17**, 159–175.

- Mayzlin, Dina. 2006. Promotional chat on the internet. *Marketing Science* 25(2) 155–163.
- Montagne, R., 2006, “Video Game Industry Thrives,” Digital Culture.
- Nelson, P., 1970, “Advertising as Information,” *Journal of Political Economy*, 82(4), 729–754.
- Pidgeon, B., and D. Hu, 2003, “U.S. Console Gamers Survey: Consumer Interest Justifies Online Initiatives,” Zelos Group.
- Piller, Charles. 1999. Internet awash in opinions; regular consumers posting evaluations on web sites. *Chicago Sun-Times* December 7, Pg. 36.
- Reimer, J., 2005, “Cross-platform game development and the next generation of consoles,” *Ars Technica*.
- Reinstein, D. A., and C. M. Snyder, 2005, “The influence of expert reviews on consumer demand for experience goods: A case study of movie critics,” *Journal of Industrial Economics*, LIII(1), 27–51.
- Resnick, Paul, Richard Zeckhauser. 2002. Trust among strangers in internet transactions: Empirical analysis of ebay’s reputation system. Michael R. Bay, ed., *The Economics of the Internet and E-Commerce, Advances in Applied Microeconomics*, vol. 11. Elsevier Science.
- Rysman, M., 2004, “Competition between networks: A study of the market for yellow pages,” *Review of Economic Studies*, 71(2), 483–512.
- Schilling, M. A., 2003, “Technological Leapfrogging: Lessons from the U.S. Video Game Console Industry,” *California Management Review*, 45(3), 6–33.
- Sochay, S., 1994, “Predicting the performance of motion pictures,” *Journal of Media Economics*, 7, 1–20.
- von Hippel, Eric. 2001. Innovation by user communities: Learning from open source software. *Sloan Management Review* 42(4) 82–86.
- Walsh, E., 2000, “Entertaining Young Net Surfers,” Jupiter Research.
- Zhang, X. M., 2006, “The lord of the ratings: Is a movie’s fate influenced by professional and amateur reviews?,” mimeo.

APPENDIX: DERIVE ELASTICITIES

As $s_{0t} = 1 - \sum_{j=1}^J s_{jt}$, we have $\frac{ds_{0t}}{ds_{jt}} = -1$. Let $G(p_{jt}) = \ln(s_{jt}) - \ln(s_{0t}) - (\beta_0 + \beta_1 \ln(p_{jt}) + \sigma \ln(s_{jt|g}) + \omega)$, where $\omega = R_{jt}\Gamma + \theta_{jt} + \eta_j + \varepsilon_{jt}$. By implicit function theorem, we have

$$\begin{aligned} \frac{ds_{jt}}{dp_{jt}} &= -\frac{dG}{dp_{jt}} / \frac{dG}{ds_{jt}} \\ &= \frac{\beta_1/p_{jt}}{\frac{1}{s_{jt}} + \frac{1}{s_{0t}} - \sigma \frac{1-s_{0t}}{s_{jt}} \frac{1-s_{0t}-s_{jt}}{1-s_{0t}}} \end{aligned}$$

Therefore, the market share elasticity with respect to price, l_p , is

$$\begin{aligned} l_p &= \frac{ds_{jt}}{dp_{jt}} \frac{p_{jt}}{s_{jt}} \\ &= \frac{\beta_1}{1 + s_{jt}/s_{0t} - \sigma(1 - s_{jt|g})} \end{aligned}$$

Similarly, assuming the coefficient for the logarithm of the average rating is γ , the market share elasticity with respect to rating, l_r , is

$$l_r = \frac{\gamma}{1 + s_{jt}/s_{0t} - \sigma(1 - s_{jt|g})}$$

