Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics

Feng Zhu
Assistant Professor
Marshall School of Business
University of Southern California
Phone: 213-740-8469
Email: fzhu@marshall.usc.edu

Xiaoquan (Michael) Zhang
Assistant Professor
HKUST Business School and
MIT Center for Digital Business
Phone: +852-2358-7644
Email: zhang@ust.hk

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Abstract

We examine how product and consumer characteristics moderate the influence of online consumer reviews on product sales using data from the video game industry. The findings indicate that online reviews are more influential for less popular games and games whose players have greater Internet experience. The paper shows differential impact of consumer reviews across products in the same product category, and suggests that firms’ online marketing strategies should be contingent on product and consumer characteristics. We discuss the implications of these results in light of the increased share of niche products in recent years.

Keywords: Online consumer reviews; Word of mouth; Internet marketing; Long tail
Consumers commonly seek quality information when purchasing new products. With the Internet’s growing popularity, online consumer reviews have become an important resource for consumers that are seeking to discover product quality. A recent survey by comScore, an Internet marketing-research company, finds that 24% of Internet users access online reviews prior to paying for a service delivered offline.\(^1\) Accordingly, many firms are taking advantage of online consumer reviews as a new marketing tool (Dellarocas 2003). Studies show that firms not only regularly post their product information and sponsor promotional chats on online forums such as USENET (Mayzlin 2006), but also proactively induce their consumers to spread the word about their products online (Godes and Mayzlin 2004). Some firms even strategically manipulate online reviews in an effort to influence consumers’ purchase decisions (Dellarocas 2006).\(^2\)

An underlying belief behind such strategies is that online consumer reviews can significantly influence consumers’ purchasing decisions. Several studies, as summarized in Table 1, show that professional reviews can significantly influence consumers’ decisions. With the proliferation of online review systems, many people believe that online consumer reviews could be a good proxy for overall word of mouth (WOM) and could also influence consumers’ decisions. Empirical findings support this idea. For example, Godes and Mayzlin (2004) find a positive relationship between online WOM and TV show viewership. Liu (2006) studies movie reviews and finds that online movie reviews offer significant explanatory power for both aggregate and weekly box office revenues. Dellarocas et al. (2007) find that adding online movie ratings to their revenue-forecasting model significantly improves the model’s


\(^2\)For example, a New York Times story revealed that some prominent authors had apparently pseudonymously written themselves five-star reviews (Harmon 2004).
predictive power. These studies generally suggest that many consumers make offline purchase decisions based on online information and at least some aspects of online WOM are proxies for overall WOM.

The efficacy of online reviews could nonetheless be limited. First, online reviews may merely represent consumers’ preferences. These reviews may predict product sales but have little influence on consumers’ decisions. In the terms of Eliashberg and Shugan (1997), online reviews in this case serve as predictors rather than influencers of product sales. Second, reviewers are not a randomly drawn sample of the user population. Anderson (1998) finds that extremely satisfied and extremely dissatisfied customers are more likely to initiate WOM transfers. Li and Hitt (forthcoming) find potential bias in consumer reviews during early product-introduction periods. Finally, interested parties can easily manipulate online forums. Dellarocas (2006) and Mayzlin (2006) theoretically analyze the scenarios in which firms can anonymously post online reviews to praise their products or to increase awareness about them. As a result, potential buyers may heavily discount online reviews.

Several recent studies, summarized in Table 2, attempt to identify the relation between online consumer reviews and product sales, and they generate mixed findings. For example, in an online experiment, Senecal and Nantel (2004) find that participants who consulted product recommendations selected recommended products twice as often as those who did not consult recommendations. Chevalier and Mayzlin (2006) find that online consumer ratings significantly influence product sales in the book market and that customers actually read review text in addition to the reviews’ summary statistics. Zhang and Dellarocas (2006) obtain similar results in the movie industry. In contrast, Chen et al. (2004) and Duan et al. (2008) find that online reviews do not influence sales and only serve as predictors.

Different from these studies that focus on the average effect of online reviews on product
sales, in this paper, we examine contextual factors that moderate the relation between the
two. We propose a conceptual framework and hypothesize that product- and consumer-
specific characteristics affect consumers’ reliance on online consumer reviews and thus are
important factors governing the efficacy of online reviews. Using a data set on sales and
consumer reviews of video games, we find that online consumer reviews have a greater
influence on the sale of games whose players have more Internet experience. In addition,
online reviews are significantly more influential in affecting sales of less popular games than of
more popular games. Interestingly, we also find that the influence of online reviews becomes
greater after the early months of introduction.

Our study is the first to empirically demonstrate the differential impact of consumer
reviews across products in the same product category. The results suggest that firms’ online
marketing strategies may not be effective for all types of products, even if they are in the
same category. This implication contrasts with the extant view that firms need to actively
manage online WOM, given the great efficiency of the Internet in spreading WOM, and that
they should also strategically respond to online consumer reviews (e.g., Chen and Xie 2005,
Dellarocas 2006).

Our study also suggests that niche producers and producers that sell mostly via online
channels should be more concerned about online consumer reviews and manipulations of
online review systems, because online reviews could significantly affect their sales. As the
proliferation of online markets has led to the emergence of many niche producers, a phe-
omenon often dubbed the “long tail” (Anderson 2006), this study’s results have important
implications for their survival.

In the following sections, we develop our conceptual framework and provide background
information about the video game industry and the cross-platform development of video
games. After discussing the data sources, we develop an empirical strategy and present the
results. We conclude with a discussion of the implications of our findings.
We focus on single-purchase products in our study. Information goods, such as books, movies, music, computer games, are examples of products purchased only once. Many of these single-purchase products can be considered experience goods (Nelson 1970), whose product characteristics are difficult to observe until consumption. Online reviews thus could be useful in reducing the risk of purchasing such products. Figure 1 depicts our conceptual framework. Online reviews are expected to influence product sales only when consumers’ reliance on online reviews is sufficiently high when they make purchase decisions. The degree of reliance, in turn, depends on product- and consumer-specific characteristics. In addition, other factors, such as competition, business models (e.g., business-to-consumer or consumer-to-consumer), or even the online review system’s design (e.g., how ratings are displayed, or how easy it is to rate an item) may affect consumers’ reliance on reviews.

The framework is closely related to the psychological choice model discussed in Hansen (1976), in which the effectiveness of an influencer (online reviews) is moderated by environmental and contextual factors (consumer and product characteristics), and the interactions among these variables eventually determine the response (purchase decisions). Consistent with this framework, several studies show that consumers’ use of different information sources indeed varies with product characteristics. Beatty and Smith (1987) find that consumers’ search effort is influenced by their product knowledge. Reinstein and Snyder (2005) find that professional reviews have a significant effect on opening weekend box-office revenue for narrowly released movies and for dramas, but not for widely released movies, or for such genres as action movies or comedies. Cheema and Papatla (forthcoming) find that the relative importance of online information is higher for utilitarian products than for hedonic products. Studies also point to the important effect of consumer characteristics on the re-
liance on certain information sources. For example, Westbrook and Fornell (1979) show that consumers’ background characteristics, such as education attainment, will affect their need for information related to purchase decisions. Klein and Ford (2003) find that consumers’ online experience moderates their trust in different information sources.

Similar to these studies, we adopt the view that product- and consumer-specific characteristics can significantly moderate the relation between online reviews and purchase decisions. In our study, we focus on product popularity (measured by the products’ sales) as the product-specific characteristic and consumer Internet experience (measured by the length of time consumers have been using the Internet) as the consumer-specific characteristic.

**Product Popularity**

Online consumer reviews could have a greater impact on the sales of popular products for several reasons. First, popular products tend to receive more reviews and having a large number of reviews makes such online reviews seem more trustworthy. As Kirby (2000) explains, one “may not trust just one nonexpert...but if 9 out of 10 nonexperts agree, it’s probably worth buying.” Chen et al. (2004) confirm that an increase in information sources could lead to more trust. They show that as the number of consumer reviews increases, the overall rating converges to the true quality. Therefore, reviews of popular products could more accurately reflect product quality and thus could be more influential.

Second, given the large number of reviews popular products receive, consumers may be more confident that they can find reviews for a popular product online (Elberse and Eliashberg 2003) and thus are more likely to search for online reviews for popular products. Disproportionately more searches are likely to increase the influence of these reviews. In contrast, if consumers believe that reviews of less popular products are rare and hard to find, they may not search for such reviews at all. Reviews of less popular products would then have little impact on their purchase decisions.
Finally, reviews of popular products could have a greater effect on consumers’ decisions because consumers are exposed to these reviews more often. Extant studies suggest that mere exposure is sufficient to create a favorable feeling and can be interpreted as a preference later (Zajonc 1980, Bornstein 1989). Along this line, Janiszewski (1993) finds that the mere exposure effect persists even when initial exposure to brand names and product packages is unintended. As popular products are discussed more frequently than less popular products, and consumers are exposed to them repeatedly, the exposure effect could have a significant impact on consumer purchasing behavior.

The discussion above suggests that both the ratings and the number of reviews could be more salient for popular products. We therefore hypothesize:

\[ H_{1a}: \text{The relations between online reviews (e.g., online ratings and the number of online reviews) and product sales are stronger for popular products than for less popular products.} \]

In contrast, online consumer reviews may be less influential for popular products. First, consumers may have a lower need to resort to online reviews for popular products. One major reason consumers use online reviews is to obtain quality information to reduce risk (Pavlou and Gefen 2004, Bolton et al. 2004). Being popular in itself signals higher quality. Previous studies show strong linkages between a product’s popularity and its perceived quality. For example, Caminal and Vives (1996) develop a model based on market signaling in the presence of imperfect information and find that future consumers interpret popularity or large market shares as a signal of high quality. Hellofs and Jacobson (1999) suggest several mechanisms through which popularity may influence perceived quality, such as signaling, creating network externalities, and inclusion as an attribute in consumer’ quality functions.

Studies also show that purchasing popular products tends to minimize potential risk. DeSarbo et al. (2002) argue that consumers prefer popular products because popularity rep-
resents a type of social cue, and following the social cue tends to reduce perceived risk. In a similar vein, the literature on herding suggests that it is sometimes optimal for consumers to ignore or not seek private information and follow the crowd (e.g., Banerjee 1992, Bikhchandani et al. 1992).

Since popularity itself testifies to a product’s quality and reduces uncertainty about its purchase, individuals may perceive that popular products are significantly less risky than less popular products. The use of risk-handling activities is positively correlated with the amount of perceived risk (Dowling and Staelin 1994). We would thus expect consumers to conduct fewer risk handling activities (such as reading online reviews) for popular products. Hence, online reviews will be less influential for popular products.

From a different perspective, the literature on consumer decision-making (e.g., Josephs et al. 1992, Zeelenberga et al. 1996, Zeelenberga and Beattieb 1997) suggests that consumers take greater responsibility for negative outcomes when their actions deviate from the norm or the default option. In the context of consumer purchase decisions, Simonson (1992) shows that consumers feel more regret if they choose a lesser-known brand that turns out to be inferior than if they choose a well-known brand that turns out not to be better than the lesser-known option. In anticipation of such regret, consumers interested in a less popular product are likely to search and access more WOM information to shield themselves from possible regret.

Finally, consumers use a mix of online (e.g., online reviews, blogs) and offline (e.g., family and friends, salespeople, and magazines) WOM information to help structure their decisions. Past research shows that WOM effectiveness depends on the strength of ties, or the closeness of the relationship between the recommendation source and the consumer who makes the decision. Strong ties are perceived as more influential than weak ties, and they are more likely to be utilized as sources of information (Brown and Reingen 1987). In the case of offline WOM, such as recommendations from friends and family members, consumers could
use source similarity and expertise to determine the credibility of information (Chatterjee 2001). In an online environment, however, “tie strength” is typically much weaker, because recommendations are from total strangers, and it is difficult for consumers to determine the information’s credibility. Indeed, experimental evidence shows that when both channels are present, the offline channel is generally preferred over the online channel (Frambach et al. 2007). As popular products are more likely to be featured in offline channels such as magazines and store demos, and discussed among friends, their consumers may not resort to online reviews for quality information, and hence are less likely to be influenced by online reviews.

The discussion above suggests that online reviews could be more effective in influencing the purchases of less popular products, because consumers are more likely to seek quality information to minimize the purchase risk and the likelihood of post-purchase regret, and such quality information is likely to be unavailable from offline channels. It is therefore an empirical question whether online reviews are more influential for popular or less popular products. We propose the following competing hypothesis:

**H1b:** The relations between online reviews (e.g., online ratings and the number of online reviews) and product sales are stronger for less popular products than for popular products.

**Consumer Internet Experience**

The Internet significantly reduces search costs (Brynjolfsson and Smith 2000) and enables the convenient comparison of various alternatives (Keeney 1999). Consumers with greater Internet experience are more likely to use online channels to collect product information, because their cost of collecting information from the online channel is likely to be lower than that from the offline channel (Cook and Coupey 1998). Several field studies confirm
that Internet experience is positively correlated with the frequency of using the Internet to gather information (e.g., Kehoe et al. 1999, Palmquist and Kim 2000, Weiser 2000) and search performance (e.g., Lazendorf et al. 2000). Similarly, Novotny (2004) studies how users search information online and finds that a lack of Internet experience affects user persistence and often leads to quick abandonment of the Internet as an information source. These studies suggest that consumers with greater Internet experience would be more likely to access online reviews.

Research also shows that a consumer with greater Internet experience is likely to have a different perception of the attributes of the online channels compared to an Internet novice and the consumer may have greater confidence in the Internet (Bart et al. 2005). For an Internet novice, in contrast, using online information may evoke perceptions of uncertainty and complexity. Internet experience may, therefore, moderate the evaluation of online information.

Hence, as consumers with more Internet experience are more likely to use the Internet as their primary information source and are more likely to have greater confidence in the Internet, they are more likely to be influenced by online reviews. We thus hypothesize:

\[ H_{2a} : \text{The relations between online reviews (e.g., online ratings and the number of online reviews) and product sales are stronger for products targeting consumers with greater Internet experience.} \]

At the same time, however, consumers with greater Internet experience may find online information to be less credible. As anyone can provide information online, the quality of such information tends to vary significantly. An experienced online user is more likely to have been exposed to information sources with lower reliability or to have encountered negative experiences. As a result, while a novice may easily trust online opinions, Internet veterans are not nearly as easily influenced. Consistent with this argument, Cheema and
Papatla (forthcoming) analyze data from a telephone survey and show that consumers with greater Internet experience have diminished interest in online sources. Similarly, through a survey conducted with automobile shoppers and purchasers, Klein and Ford (2003) find that experienced online consumers rate offline information sources as significantly more credible than online sources.

In addition, consumers with greater Internet experience can easily find many reviews about a product from multiple sources. Assessing the validity of these information sources, however, imposes significantly higher cognitive costs. To deal with the information overload problem, consumers are more selective about the types of information to which they respond (Rust and Chung 2006). As a result, the relation between online reviews and their purchase decisions could be weaker.

Therefore, because consumers with greater Internet experience lack trust in online information and information overload carries a high cognitive cost for them, they are not as easily influenced by online reviews. We hypothesize:

$H_{2b}$: The relations between online reviews (e.g., online ratings and the number of online reviews) and product sales are stronger for products targeting consumers with less Internet experience.

In the context of video games, because such games have different genres and storylines, they may or may not offer an online multi-player mode. In the online mode, a player can connect through the Internet with other players and interact with them in real time. We subsequently refer to those games with both an online mode and an offline mode as “online games” and those with only an offline mode as “offline games.” Playing games online requires not only a fast Internet connection but also good skills in coordinating and communicating online with other players in real time. Thus, we expect consumers purchasing online games, on average, to have greater Internet experience. Indeed, studies find a positive relationship
between the frequency of playing online games and the frequency and length of Internet usage (e.g., Lo et al. 2005). We could therefore test $H_{2a}$ and $H_{2b}$ by examining the differential impact of online reviews on the sales of online and offline games.

**Video Game Industry and Cross-platform Game Development**

The video game industry is becoming increasingly important today, and its growth far outpaces other entertainment industries, such as movies and music.\(^3\) From 2003 to 2006, the video game software industry’s annual growth rate exceeded 17%, in contrast to the US economy’s 2% growth rate over the same period.\(^4\) The industry’s annual revenue was about $17.94 billion dollars in 2007,\(^5\) which was almost double the box-office revenue in the motion picture industry. Halo 3, the best-selling game title of 2007, took in more revenue ($170 million) in its first day of sales than the biggest opening weekend ever for a movie (Spider-Man 3, $150 million).\(^6\) The penetration rate of video game consoles is also very high: About 41% of US households owned video game consoles in 2006.\(^7\) Our study thus not only enriches the literature on online reviews, but also offers insights into this important sector for marketing practitioners.

The role of reviews is potentially greater for video games than for movies. First, there are more game titles than movie titles. In 2007, the Entertainment Software Rating Board


\(^6\)Snider, Mike, “ ‘Halo’ takes industry to new heights; Early sales slash gaming records,” USA Today, September 27, 2007.

(ESRB) gave out 1,563 ratings to a subset of all games produced that year. Facing so many choices, a game player would need to invest substantial time and energy to identify good games. Second, a video game typically costs more than a movie. According to NPD Fun Group estimates, the average selling price of a game was $38.36 at the end of 2007. As most gamers are young and have limited incomes, they frequently use reviews to avoid bad purchases (Bounie et al. 2005). It is therefore not surprising that Game Informer, a magazine featuring articles, news, and reviews of popular video games, ranks among the most highly circulated magazines, and game-review web sites, such as GameSpot.com, are consistently ranked among the top 100 most popular web sites in the United States.

Publishers usually fund game development. 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 developed for a single console, and whenever a game was ported to a new console, a different team would have to rewrite the entire game. Development teams would use assembly language, a human-readable notation for the machine language, to write most games at that time, as this language optimized the processing speed and required very little overhead. Today, as processing speed is no longer a critical issue, high-level languages, such as C++ and Java, are the most popular game development languages (Goodwin 2005). In addition, although code libraries for different consoles are not compatible, game developers can take advantage of cross-platform

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8Source: ESRB. Available at http://www.esrb.org/ratings/faq.jsp, accessed August, 2008. ESRB releases game ratings that are designed to provide “concise and impartial information” about the content in computer and video games. These ratings are similar in nature to the MPAA ratings for movies.


middleware platforms (e.g., Criterion’s Renderware 3D development platform) to program a game in a single language and port the game onto several consoles. Many publishers no longer see delayed cross-platform development as an option. Instead, they often mandate that developers release games on all three major console platforms simultaneously (Reimer 2005).

We restrict our analysis to games that are developed for both Sony’s PlayStation 2 and Microsoft’s Xbox for two reasons. First, during the period for which we have review data, PlayStation 2 and Xbox were the two largest players in the 128-bit console market and had the largest game libraries. Second, both consoles target adults between 18 and 34, positioning themselves directly against each other; therefore, we expect the two gaming populations to be very similar. Table 3 compares features of the two consoles. The only major differences between them are clock speed and the amount of memory.

[Table 3 about here.]

Empirical Analysis

Data

Data on console sales and game sales come from the NPD Fun Group (NPD hereafter), a leading market research firm that tracks this industry. NPD collects data from approximately 17 leading retail chains that account for 80% of the US market. From these data, NPD formulates estimates of sales figures for the entire US market. We obtain monthly data for PlayStation 2 and Xbox and their associated games from October 2000 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.

\footnote{See Schilling (2003) for an overview of the evolution of different console generations.}
We gather review data from GameSpot.com (also known as VideoGames.com). According to Alexa.com, a web site providing an online traffic monitoring service, GameSpot.com is the 65th most-visited site in the US as well as the most popular one for video games, reaching over 10 million unique gamers each month. 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 publishing player reviews. To ensure the quality of these reviews, only paid subscribers or users with a sufficient level of experience (as demonstrated by their participation in other parts of the site, such as forums) are allowed to post them. A maximum of 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.

For each of five aspects (gameplay, graphics, sound, value, and reviewer’s tilt), reviewers use a scale ranging from 1 to 10 for their reviews, with 10 being the best and 1 being the worst. For each review, GameSpot publishes the weighted average of all five aspects. We use this weighted 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 which are published within a month after the games are released. The reviews by the editors at GameSpot and from other sources are rarely updated after they are published, and therefore they vary little 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. Even for the same game titles, player reviews are generally different across consoles.

We collect reviews for each game in each month between March 2003 and October 2005.

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15We also looked at other less popular game web sites. Almost all of them provide only professional reviews.
Following previous research on consumer reviews (e.g., Chevalier and Mayzlin 2006, Zhang and Dellarocas 2006), we focus on three review variables: average rating, the coefficient of variation of ratings and total number of reviews. The average rating reflects the level of consumer satisfaction and is the focus of most empirical studies on product reviews. The coefficient of variation, measured as the ratio of the standard deviation to the mean rating, captures the degree of disagreement among consumers. High variation carries both great risk and great reward, while low variation offers a safe bet. Past research shows that for different products, variation of consumer reviews may be positively or negatively associated with product sales (e.g., Martin et al. 2008, Sun 2008). We also collect the total number of reviews as a measure of the volume of discussions. The number of reviews captures the exposure effect and may signal game’s popularity.

Although GameSpot offers a convenient way to measure online WOM, its reviews may not be representative of all online opinions on specific games. Players also can obtain review information from other channels, such as online bulletin boards and chat rooms. Therefore, our current estimate could underestimate the relationship between reviews and sales. Had we been able to consider all sources of information, our conclusions would be strengthened.

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

**Empirical Methodology**

An inherent problem in measuring the influence of reviews on product demand is that products receiving positive reviews tend to be of high quality. Since quality is often unobserved by researchers, it is difficult to determine whether the review or the quality is responsible for the high demand. Therefore, positive correlations found between reviews and product sales in some of the earlier studies could be spurious.

Recent studies propose several methods to circumvent this problem. For example, Einav (2007) and Zhang and Dellarocas (2006) use fixed-effects specifications to control for unobs-
served movie quality. Reinstein and Snyder (2005) take advantage of the timing of critics’ reviews relative to a movie’s release and find that the measured influence effect is small but still detectable. Chevalier and Mayzlin (2006) examine book reviews and sales ranks on Amazon.com and BN.com at several time points and use a differences-in-differences approach to eliminate book- and book-site-specific effects.

In this paper, similar to Chevalier and Mayzlin (2006), we adopt a differences-in-differences approach. Our empirical analysis hinges on the video games that are released for two different consoles: PlayStation 2 and Xbox. By taking the differences between the sales of the same game title for the two consoles, we eliminate unobserved common factors, such as game characteristics, that may affect both reviews and sales on both consoles. By examining the differences across consoles over time, we control for console-specific factors, such as the underlying taste difference between the console-installed bases, that may influence both reviews and sales. A game title often receives different reviews on the two consoles. Consider a situation in which a game title receives better reviews on one console than on the other: The differences-in-differences approach enables us to test whether the game title’s sales on one console increase relative to the same game title’s sales on the other console is a result of differences in reviews.

Our analysis differs from that of Chevalier and Mayzlin (2006) in several aspects. First, the two studies focus on different questions. Chevalier and Mayzlin (2006) look at online reviews’ aggregate influence, while we examine how product and consumer characteristics may moderate the influence of online reviews. Second, our empirical strategy explicitly controls for competition among games by estimating a nested logit demand model. The demand for a game is likely to be affected by the number of competing games on the market, and the intensity of this substitution effect may vary across consoles and over time. Firms’ pricing strategies may adjust according to the intensity of competition; therefore, it is important to capture this effect to obtain unbiased estimates from a demand equation. In Chevalier and
Mayzlin (2006), the demand for individual books is implicitly assumed to be independent of that of their competitors, although in reality, the availability of books in the same category is likely to affect the demand for a particular book. Third, our sales data of games cover the whole US market, while Chevalier and Mayzlin (2006) only look at book sales on two web sites and approximate book sales using ranks. Our results thus capture the effects of online reviews on purchase decisions made both online and offline. Finally, our data include all games with positive sales in each month, while book data used in Chevalier and Mayzlin (2006) are truncated, because Amazon.com and BN.com do not report rank data for books with low popularity. Therefore, we cannot fruitfully test hypotheses related to product popularity with book data.

We now proceed to describe our two-stage nested logit demand model for games. We assume that there are $J$ games available for 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. In the first stage, a player first decides whether to purchase a game. In the second stage, if he chooses to purchase a game, he then decides which game to purchase. For any given game, he has at most unit demand. The perceived utility of player $i$ from purchasing a game $j$, $j \in [1, J]$, for console $k$ at time $t$, $u_{ijkt}$, is affected by game price, perceived game quality and other game characteristics. Our conceptual framework suggests that perceived game quality is affected by a combination of consumer reviews, game popularity, and the player’s Internet experience. We employ two different measures of popularity. The first measure is a cross-sectional dummy variable that equals 1 if the game’s aggregate sales across the two consoles are greater than the mean performance of all games in the month. The second measure captures the inter-temporal pattern of games’ life-cycles, because the popularity of a video game often drops rapidly after its release. The average life-cycle of all games is about 33 months, but on average, more than 50% of game sales occur within the first four months after a game’s release. For any game, the first four months after release could therefore
be considered the time period in which it is popular. Therefore, the dummy variable takes
the value of 1 when the game is in the first four months of its life-cycle. To operationalize
consumer Internet experience, we create a dummy variable indicating whether a game can
only be played offline or not. Other variables, such as market share, prices, and game
characteristics, can be obtained directly from the original data set. Hence, we express the
player’s utility, $u^k_{ijt}$, as a function of price ($p^k_{jt}$), lagged review variable ($r^k_{j,t-1}$)\(^{16}\), a dummy
indicating whether a game is popular ($\text{popular}_{jt}$), a dummy indicating whether a game can
only be played offline ($\text{offline}_j$), and other game characteristics ($\xi^k_{jt}$):

$$
\begin{align*}
  u^k_{ijt} = & \beta_0 + \beta_1 p^k_{jt} + \beta_2 r^k_{j,t-1} + \beta_3 (r^k_{j,t-1} \times \text{popular}_{jt}) + \beta_4 (r^k_{j,t-1} \times \text{offline}_j) + \\
                  & \beta_5 \text{popular}_{jt} + \beta_6 \text{offline}_j + c^k_{ijt} + \zeta^k_{jgt} + (1 - \sigma) \nu^k_{ijt}.
\end{align*}
$$

The two dummy variables, $\text{popular}_{jt}$ and $\text{offline}_j$, indicate different sub-groups among the
all video games. As our conceptual framework suggests that the review variable’s effect
is conditional on the type of product, we interact the review variable with these dummy
variables. With these interaction terms, we are able to measure the effects of online reviews
of different types of products (Aiken and West 1991). For example, $\beta_2$ measures the influence
of the reviews on games with $\text{popular}_{jt} = 0$ and $\text{offline}_j = 0$ (i.e., less popular and online
games). Similarly, $\beta_2 + \beta_3$, $\beta_2 + \beta_4$ and $\beta_2 + \beta_3 + \beta_4$ measures the influence of consumer
reviews on popular and online games, less popular and offline games, and popular and online
games, respectively. We also include two unobservables, $c^k_{jgt}$ and $\nu^k_{ijt}$. $c^k_{jgt}$ represents player
utility common to all games of group $g$. $\nu^k_{ijt}$ 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.

\(^{16}\)We use one review variable here to illustrate our methodology for simplicity. In the regression analysis,
we use multiple review variables each interacting with the dummy for game popularity and the dummy for
offline games.
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 use an additive separable functional form in Model (1) for a couple of reasons. First, this form enables us to capture the moderating effects easily using the interaction terms. Second, the additive separable functional form yields a linear regression specification as we discuss below. We could therefore use straightforward instrument variable methods to handle endogenous variables such as game prices (Berry 1994).

We normalize the utility from the outside good to be zero. As game players need to have a game console before they can play games developed for this console, we use the size of the installed base of each console as the potential market. Also, as the two consoles are incompatible (i.e., games developed for one console cannot be played on the other), the potential market for games is console-specific. We denote the share of the potential market captured by game $j$ of console $k$ in period $t$ as $s^k_{jt}$ and game $j$’s share of the portion of the market that purchases games in period $t$ (i.e., the share of game $j$ within group $g$) as $s^k_{jtg}$. Thus, $s^k_{jtg}$ can be computed as $s^k_{jt}/(1 - s^0_{jt})$, where $s^0_{jt}$ is the market share of the outside option in period $t$ for console $k$. Following Berry (1994) and Cardell (1997), the demand equation for the two-stage nested logit model can be derived as:

$$\ln(s^k_{jt}) - \ln(s^k_{0t}) = \beta_0 + \beta_1 p^k_{jt} + \beta_2 r^{k}_{j,t-1} + \beta_3 (r^{k}_{j,t-1} \times \text{popular}_{jt}) + \beta_4 (r^{k}_{j,t-1} \times \text{offline}_{j}) + \beta_5 \text{popular}_{jt} + \beta_6 \text{offline}_{j} + \sigma \ln(s^k_{jtg}) + \xi^k_{jt}. \quad (2)$$

Given the panel structure of data, we decompose the component $\xi^k_{jt}$ as

$$\xi^k_{jt} = \theta_{jt} + \eta^k_{j} + \varepsilon^k_{jt}$$

\footnote{Similar logit models have been used frequently in the literature to estimate the impact of marketing mix variables on consumer purchase behaviors (see, for example, Nakanishi and Cooper 1982, Kamakura et al. 1996, Besanko et al. 1998).}
where $\theta_{jt}$ is a game-specific component that is the same for the same game across different platforms but can vary over time, $\eta^k_{jt}$ is the console-specific effect, and $\varepsilon^k_{jt}$ is an i.i.d. normal error term varying across games and over time. $\theta_{jt}$ is related to such factors as promotions by game publishers, the brands of the game publishers, and the game’s age and quality. $\eta^k_{jt}$ captures 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 differ because of difference in console characteristics, such as clock speed. Therefore, $\eta^k_{jt}$ is time invariant but may vary across games on the same console.

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

$$\ln(s^p_{jt}) - \ln(s^p_{0t}) = \beta_0 + \beta_1 p^p_{jt} + \beta_3 (r^p_{jt,t-1} \times \text{popular}_{jt}) + \beta_4 (r^p_{jt,t-1} \times \text{offline}_j) + \beta_5 \ln(s^p_{jt|g}) + \theta_{jt} + \eta^p_{jt} + \varepsilon^p_{jt},$$

$$\ln(s^x_{jt}) - \ln(s^x_{0t}) = \beta_0 + \beta_1 p^x_{jt} + \beta_3 (r^x_{jt,t-1} \times \text{popular}_{jt}) + \beta_4 (r^x_{jt,t-1} \times \text{offline}_j) + \beta_5 \ln(s^x_{jt|g}) + \theta_{jt} + \eta^x_{jt} + \varepsilon^x_{jt},$$

The within-group market shares (WGS’s), $\ln(s^p_{jt|g})$ and $\ln(s^x_{jt|g})$, are by definition endogenous and require instrument variables. Following Einav (2007), 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. Also, as the potential market size may change sharply across consoles and over time, we add the installed base of each console as a control variable in the instrument specification. In addition, game prices, $p^p_{jt}$ and $p^x_{jt}$, could be endogenous in our demand model. While we do not have cost-side variables to use as instruments, as suggested in Berry (1994) and Nair et al. (2004), we could use characteristics of competing games as instruments. For each game, we collected data on its genre (e.g., 1st
person shooter, party games, and puzzle games) and Entertainment Software Rating Board (ESRB) rating (e.g., everyone, adult only, and teen). Following the approach in Nair et al. (2004), we use the number and average age of competing games in the same genre, of competing games in the same ESRB group, and of all competing games, as well as their squared terms as instruments for game prices in each month.

The parameter $\theta_{jt}$ contains both observed and unobserved game-specific characteristics. The unobserved characteristics are likely to be correlated with price and review variables, and omitting their effects would produce biased coefficients. As $\theta_{jt}$ is the same across console systems, we eliminate the game-specific effects by differencing the data across consoles:

$$
\Delta M_{j,t} = \beta_1 \Delta p_{j,t} + \beta_2 \Delta r_{j,t-1} + \beta_3 (\Delta r_{j,t-1} \times \text{popular}_{jt}) + \beta_4 (\Delta r_{j,t-1} \times \text{offline}_{j})
$$

$$+ \sigma \Delta WGS_{j,t} + \Delta \eta_j + \varepsilon_{j,t} 
$$

where $\Delta M_{j,t} = [\ln(s^p_{jt}) - \ln(s^p_{0t})] - [\ln(s^x_{jt}) - \ln(s^x_{0t})]$, $\Delta p_{j,t} = p^p_{jt} - p^p_{0t}$, $\Delta r_{j,t-1} = r^p_{j,t-1} - r^x_{j,t-1}$, $\Delta WGS_{j,t} = \ln(s^p_{jt|g}) - \ln(s^x_{jt|g})$, and $\Delta \eta_j = \eta^p_{j} - \eta^x_{j}$.

$\Delta \eta_j$, which captures the differences in console-specific effects, is also unobserved but does not vary over time. As console differences might affect differences in game prices and reviews, we take an additional difference of Equation (5) between period $t$ and $t + 1$ and have:

$$
\Delta \Delta M_{j,t} = \beta_1 (\Delta \Delta p_{j,t}) + \beta_2 (\Delta \Delta r_{j,t-1}) + \beta_3 (\Delta \Delta p_{j,t} \times \text{popular}_{jt}) +
$$

$$\beta_4 (\Delta \Delta p_{j,t} \times \text{offline}_{j}) + \sigma (\Delta \Delta WGS_{j,t}) + \varepsilon_{j,t}.
$$

We use Equation (6) as our empirical specification.

An implicit assumption in our empirical methodology is that the price and reviews of a game on one console have minimal, if any, influence on the sales of the game with the same title on another console. As the two consoles are incompatible with each other and most
game players only own one console\textsuperscript{18} and participate in its associated online forums, we would expect that most game players read reviews for games on one console. In addition, if reviews for the two consoles have more or less the same influence on game sales, our differences-in-differences approach would eliminate their impact, and differences in the review variables should not show significant correlations with sales difference. Hence, our empirical study serves as a test for this assumption.

\textbf{Summary Statistics}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2}
\caption{Figure 2 about here.}
\end{figure}

Our final data set consists of 220 game titles that are available for the two consoles between March 2003 and October 2005. Seventy-nine of them have different release dates for the two consoles and thus are removed from the sample. Similar to other empirical studies based on discrete choice models (e.g., Argentesi and Filistrucchi 2007, Einav 2007, Rysman 2004), a natural concern is the assumption of a 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 purchase one game or less in each month, on average (Pidgeon and Hu 2003). Consumers’ purchase frequency, however, could exhibit seasonal patterns. Figure 2 shows mean revenue and mean units sold by month for all games over the sampling period. As the figure indicates, the monthly game sales exhibit strong holiday effects. We thus remove observations in November and December from our data set.

\begin{table}[h]
\centering
\begin{tabular}{ll}
\hline
\textbf{Table 4 about here.} \\
\hline
\end{tabular}
\end{table}

\textsuperscript{18} According to a 2003 survey by the NPD Group, a market research firm, among all consumers with a video game console, less than 5\% own both Xbox and PlayStation 2 consoles. Source: The NPD Group, “Video Games Cross-Platform Study,” August 2003.
Table 4 provides summary statistics for games in our sample. A t-test indicates that the monthly unit sales of games for PlayStation 2 are significantly greater than those for 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 for the two consoles are at about the same level, most likely because of the intense competition among game titles for each console: On average, in each month 475 games on the Xbox console and the 810 games on PS2 console have positive sales.

[Table 5 about here.]

Table 5 presents summary statistics of reviews as of October 2005. The data suggest that reviews are overwhelmingly positive for games for both consoles. Researchers observe similar patterns in other contexts, such as book reviews on Amazon (Chevalier and Mayzlin 2006) and reputation profiles on eBay (Resnick and Zeckhauser 2002). On average, we have more than 9 reviews for each game. The distribution of the number of reviews is skewed: The number of reviews ranges from 1 to 63 for PlayStation 2 games and from 1 to 104 for Xbox games. We find no significant difference in any of the three metrics across the two consoles, suggesting that the two gaming populations are quite similar. One 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 reviewers write reviews for both consoles.

[Figure 3 about here.]

Figure 3 shows the mean prices, units sold, and ratings for PlayStation 2 and Xbox games, respectively. In all three figures, the patterns for PlayStation 2 and Xbox are quite similar. Both average price and average units sold decline over time. The average price declines almost linearly during the first 10 months, and the average units sold also drops
significantly for the first few months.\textsuperscript{19} Average ratings in the first couple of months are significantly higher than those in later months. This pattern suggests the existence of a self-selection bias in the reviews, and is similar to those reported in Dellarocas et al. (2007) and Li and Hitt (forthcoming). 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.

Regression Results

[Table 6 about here.]

Table 6 presents the regression results based on the differences-in-differences specification in Equation 6. We use the differences of $\ln(s^k_{jt}) - \ln(s^k_{0t})$ 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.\textsuperscript{20} We find that game price negatively affects game demand, while average consumer rating has no effect on it. The small and non-significant coefficient of the within-group share suggests that video games are poor substitutes for each other, which is consistent with the finding in Nair (2007).

In Model II, we add the interactions between the average rating and game popularity, and between the average rating and game online capability. We first define the popularity of a game, \textit{popular}_{jt}, as a dummy variable, which takes the value of 1 if the sales of the game \textit{j} for both consoles are greater than the mean performance of all games in month \textit{t}. Information on each game’s online capability is collected from GameSpot. GameSpot

\textsuperscript{19}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 for both consoles appear relatively low.

\textsuperscript{20}We take the natural logarithm of price and review variables (i.e., average rating, variation of ratings and number of reviews). We use the logarithms of (the number of reviews + 1) and (the variation + 1) to handle zero reviews and ratings with no variation.
specifies whether a game has an online play mode. We also verify our data with information from game publishers’ and console manufacturers’ web sites. The coefficient of the rating variable here measures the influence of less popular and online games and is positive and significant. We also find that the influence is significantly weaker for popular games or offline games, as evidenced by the significant negative coefficients of the two interaction variables.

In Model III, we add the differences-in-differences measures of other review variables, such as the variation of the ratings and the number of reviews, and their interactions with game popularity and online capability. As product and consumer characteristics may also affect game publishers’ pricing decisions, we add the interactions of game prices with game popularity and online capability. The results suggest that the demand for popular games is less sensitive to price. The results on the rating variable are similar to those in Model II. In addition, we find that the number of reviews has a positive effect on less popular and online games. One possible explanation is that having a large number of reviews signals a game’s popularity. This result also likely is caused by the presence of direct network effects: For games that can be played online, players are more likely to purchase games that have been bought by many others. The effect of the number of reviews becomes weaker for offline games.

In Models IV and V, we employ an inter-temporal measure of game popularity. Instead of measuring popularity by comparing different games in each month, we define popularity for a given game over its life-cycle. In these two models, we consider a game to be popular if it is less than four months old, and less popular otherwise. We replicate the analyses in Model

\[21\] On a more technical note, online play requires online platforms (often provided by either console manufacturers or game publishers). As online platforms designed for one console may not be useable for a different console, sometimes a game can be played online on one console before it can be played online on the other. In addition, not all games can be played online at the time of their releases. Game players in general are aware of the online capability of the games (as it is often included in the game descriptions). Even if the online capability of a game is not supported at the time of purchase, they often anticipate that they can play it online in the near future. Hence, we define online games or offline games based on their online capability (instead of whether the games are actually being played online).
II and III with this new measure and obtain similar results. The results suggest that online reviews are less influential in the early phases of game life-cycles. The result is interesting in light of past research suggesting that product promotions, are more effective in the early stages of a product’s life-cycle, as uncertainty and the need for information tend to be high (Sethuraman and Tellis 1991). If we evaluate the possible effects of advertising or WOM through the lens of the Bass (1969) diffusion model, we should expect the effects to be greater in the early stages of introduction. One plausible explanation is that, in entertainment industries, the heavy use of other promotional strategies through offline channels in the early stages of product life-cycles reduces consumers’ reliance on online reviews.

[Table 7 about here.]

The coefficients of the price variable and the review variables in Table 6 measure their influence on less popular and online games. We can use the regression results to compute their influence on other types of games (e.g., popular and online games, popular and offline games, and less popular and offline games). Table 7 summarizes the results (based on Model III in Table 6). The results show that the sales of less popular games are negatively affected by their prices. The coefficients of the average rating and the variation of rating are significant only for less popular and online games. Finally, the coefficient of the number of reviews is significant for online games.

These results suggest that all three aspects of the reviews, the average rating, the variation of rating, and the number of reviews, affect the sales of less popular and online games. Our results are more comprehensive than those in existing studies, because most of these studies only look at one or two aspects of online reviews. For example, Duan et al. (2008) and Chen et al. (2004) consider the average rating and the number of reviews only, and Godes and Mayzlin (2004) focus on the volume of conversations in each newsgroup. In addition, many studies find that only one or two aspects of online reviews affect product sales. For
example, Duan et al. (2008) find that the volume of online reviews matters, but the average rating does not. In contrast, we show that for products that are less popular and targeted at consumers with great Internet experience, all three aspects could matter.

Overall, our regression analysis finds support for $H_{1b}$ and $H_{2a}$.

**Discussion and Conclusion**

**Managerial Implications**

Understanding how online reviews affect consumers’ purchase decisions is vitally important to firms that rely on online WOM to disseminate information about their products. We find that, for video games, online reviews are more influential for less popular and online games. Our empirical results support the view that the impact of online consumer reviews on product sales depends on product- and consumer-characteristics. Hence, firms’ online marketing strategies need to adjust accordingly.

The finding that online reviews are more influential for less popular games suggests that the reviews’ informational role becomes more salient in an environment where alternative means of information acquisition are relatively scarce. As such, marketers of less popular products may benefit more from allocating resources to managing online consumer reviews. Due to the scarcity of available information about niche products, even one negative review can be detrimental. Since superior online WOM translates more easily into sales for niche products, the existence of online review systems gives a great incentive for niche market producers to exert efforts to maintain good reputations. These results are particularly useful in light of niche products’ increased market share in recent years, owing to virtually unlimited “shelf space” in online markets. Recent studies (e.g., Anderson 2006, Brynjolfsson et al. 2005) show that as a result of the Internet, the economy is increasingly shifting away from a relatively small number of mainstream products at the head of the demand curve, and
toward a huge number of niches in the tail, a phenomenon often dubbed the “long tail.” For example, Brynjolfsson et al. (2006) find that obscure book titles, which are not available in typical conventional bookstores, account for about 40% of Amazon.com’s book sales in 2000. While the Internet has increased the collective share of niche products, it does not necessarily guarantee the survival of firms producing niche products. Elberse and Oberholzer-Gee (2006) and Elberse (2008) find that from 2000 and 2005, although the number of video titles selling only a few copies every week increases almost twofold during this period, the number of non-selling titles rises rapidly and becomes four times as high as in 2000. As many niche products are only sold online and their buyers are more likely to use online review systems as the primary source for quality information, our study suggests that online WOM could significantly contribute to dispersion in the tail. It is therefore crucial for niche-product producers to devote their marketing effort to online review systems when they take advantage of online channels to sell their products.

This study also finds evidence to support that online reviews are more influential when consumers have relatively greater Internet experience. Echoing the discussion in the conceptual framework about users’ Internet experience, our empirical results suggest that, at least in the video games market, the benefits of reduced search costs (Brynjolfsson and Smith 2000) and greater confidence in using the Internet (Bart et al. 2005) seem to dominate concerns about the reliability and credibility of online information sources (Klein and Ford 2003, Cheema and Papatla forthcoming). As the Internet population continues to grow, consumers inevitably become more experienced with the Internet. Our study suggests that over time, marketing managers will find online consumer reviews to be increasingly influential and thus should devote more resources to online channels.

At the same time, firms that rely heavily on using online channels to promote their products could also seek ways to reduce the search costs for online reviews. After the barrier to information acquisition becomes lower, even Internet novices could be influenced by online
reviews. For example, to reduce the search costs for reviews, Amazon has recently modified the way it reports star-levels for items. While previously it only showed an average star rating, it now shows how many people rated the item with each of the 1 to 5 stars; readers can choose to read reviews for a given star level.

Research Implications

Our research provides a potential positive reconciliation of the mixed results from previous studies. For instance, Chevalier and Mayzlin (2006) examine book sales at Amazon.com and find that online reviews influence book sales, while Chen et al. (2004), using a similar data set from Amazon.com, find the opposite. Similarly, in the context of the movie industry, Zhang and Dellarocas (2006) find that online reviews influence box-office sales but Duan et al. (2008) find the opposite. Researchers have not been able to reconcile the stark differences in results and have instead attributed them to methodological shortcomings. For example, Duan et al. (2008) point out that the mixed finding could result from the fact that researchers conduct their analyses in a cross-sectional context and do not control for unobserved differences in product quality. Our study suggests that data sets with a different mix of product types, even for the same product category, could lead to different conclusions. For example, in studying online book reviews, two data sets with different proportions of popular and less popular book titles or different proportions of technical books (whose readers presumably have greater Internet experience) and non-technical books may find that online reviews play different roles.

This work could be extended in several directions. First, future research could take a similar approach to examine the differential roles of critic reviews on various types of products within the same product category. As an example, Eliashberg and Shugan (1997) find that film critics are leading indicators of a movie’s ultimate success but do not influence its early run in the box office. Several recent studies (e.g., Basuroy et al. 2003, Reinstein and Snyder
2005), however, find that film critics can influence opening weekend box-office revenues. Heterogeneity across different movies might be a source of these divergent findings.

Second, our research suggests that online consumer reviews might significantly affect the diffusion and adoption of less popular products that target consumers with much Internet experience. Future research could therefore test whether diffusion models for forecasting the sales of such products could substantially improve their accuracy after incorporating online consumer reviews.

Third, future research could investigate firms’ online and offline marketing strategies and compare their effectiveness. Our research suggests that promotions in the offline channel may reduce the efficacy of online reviews. It is thus interesting to theoretically and empirically analyze firms’ optimal strategy in allocating marketing resources to online and offline channels.

Finally, future research could compare the influence of online reviews among multiple products. While our analysis focuses on a single product category, the results are applicable to multiple categories. For example, we expect online reviews to have a greater influence on products that are likely to be purchased or used online (e.g., software) than on those sold or used mostly offline (e.g., apparel).

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22See Table 1 for a summary of empirical studies on professional reviews and their key findings.
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Table 1: Previous Empirical Research Related to Professional Reviews

<table>
<thead>
<tr>
<th>Study</th>
<th>Method</th>
<th>Data</th>
<th>Key Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Litman (1983)</td>
<td>Multiple regression</td>
<td>Movies 1972-1978</td>
<td>Critics’ ratings are a significant factors in explaining box office revenue.</td>
</tr>
<tr>
<td>Mahajan et al. (1984)</td>
<td>Diffusion models</td>
<td>Movies 1983</td>
<td>Word of mouth was a significant predictor of attendance.</td>
</tr>
<tr>
<td>Sawhney and Eliashberg (1996)</td>
<td>Forecasting model, generalized gamma</td>
<td>Movies 1990-1991</td>
<td>Critics’ reviews are positively significant for the number of adopters.</td>
</tr>
<tr>
<td>Holbrook (1999)</td>
<td>Multiple regression</td>
<td>Movies Pre-1986</td>
<td>Ordinary consumers and professional critics emphasize different criteria in the formation of their tastes, but the correlation between popular appeal and expert judgments is positive.</td>
</tr>
<tr>
<td>Elberse and Eliashberg (2003)</td>
<td>Demand/supply model</td>
<td>Movies 1999</td>
<td>Less positive reviews correspond to a higher number of opening screens, but more positive reviews mean more opening revenue.</td>
</tr>
<tr>
<td>Reinstein and Snyder (2005)</td>
<td>Differences-in-differences</td>
<td>Movies early 1990s</td>
<td>Critics’ influence on opening weekend box office revenue is smaller than previous studies would suggest but is still significant.</td>
</tr>
<tr>
<td>Zhang and Dellarocas (2006)</td>
<td>Multiple regression</td>
<td>Movies 2003-2004</td>
<td>Critics’ influence is more significant than previously suggested, especially on early weeks’ box office revenue.</td>
</tr>
<tr>
<td>Study</td>
<td>Method</td>
<td>Data</td>
<td>Key Findings</td>
</tr>
<tr>
<td>------------------------</td>
<td>---------------------------------</td>
<td>---------------</td>
<td>-------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Resnick and Zeckhauser (2002)</td>
<td>Multiple regression</td>
<td>eBay 1999</td>
<td>Sellers with better reputations are more likely to sell their items but they enjoy no boost in price.</td>
</tr>
<tr>
<td>Chen et al. (2004)</td>
<td>Multiple regression</td>
<td>Amazon Books 2003</td>
<td>Consumer ratings are not correlated with sales.</td>
</tr>
<tr>
<td>Senecal and Nantel (2004)</td>
<td>Generalized estimating equations</td>
<td>Online Experiment</td>
<td>Participants who consulted product recommendations selected recommended products twice as often as those who did not consult recommendations.</td>
</tr>
<tr>
<td>Liu (2006)</td>
<td>Multiple regression</td>
<td>Movies 2002</td>
<td>WOM information offers significant explanatory power for both aggregate and weekly box office revenue, especially in the early weeks after a movie opens.</td>
</tr>
<tr>
<td>Dellarocas et al. (2007)</td>
<td>Diffusion model</td>
<td>Movies 2002</td>
<td>Online amateur movie ratings can be used as a proxy for word of mouth.</td>
</tr>
<tr>
<td>Duan et al. (2008)</td>
<td>Simultaneous system</td>
<td>Movies 2003-2004</td>
<td>The rating of online user reviews has no significant impact on movies’ box office revenues.</td>
</tr>
</tbody>
</table>
Table 3: **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.

<table>
<thead>
<tr>
<th></th>
<th>PlayStation 2</th>
<th>Xbox</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturer</td>
<td>Sony</td>
<td>Microsoft</td>
</tr>
<tr>
<td>Launch Date in the US</td>
<td>October 2000</td>
<td>November 2001</td>
</tr>
<tr>
<td>Price on the Launch Date</td>
<td>$299</td>
<td>$299</td>
</tr>
<tr>
<td>CD/DVD Based</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Bits</td>
<td>128</td>
<td>128</td>
</tr>
<tr>
<td>Clock Speed</td>
<td>300 MHZ</td>
<td>733 MHZ</td>
</tr>
<tr>
<td>RAM</td>
<td>38 MB</td>
<td>64 MB</td>
</tr>
<tr>
<td>Network Compatibility</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Table 4: **Summary Statistics for Games**

Panel A and B present summary statistics for games developed on both PlayStation 2 and Xbox consoles 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**

<table>
<thead>
<tr>
<th>Variable</th>
<th>No. of Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Sales (Units)</td>
<td>3,330</td>
<td>10,038.4</td>
<td>25,518.4</td>
<td>5</td>
<td>561,540</td>
</tr>
<tr>
<td>Monthly Price ($)</td>
<td>3,330</td>
<td>21.58</td>
<td>11.23</td>
<td>1.80</td>
<td>54.85</td>
</tr>
</tbody>
</table>

**Panel B: Summary Statistics for Games on Xbox**

<table>
<thead>
<tr>
<th>Variable</th>
<th>No. of Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Sales (Units)</td>
<td>3,305</td>
<td>5,499.10</td>
<td>15,816.7</td>
<td>7</td>
<td>378,194</td>
</tr>
<tr>
<td>Monthly Price ($)</td>
<td>3,305</td>
<td>21.32</td>
<td>11.10</td>
<td>1.88</td>
<td>54.79</td>
</tr>
</tbody>
</table>
Table 5: **Summary Statistics for Reviews**

Panel A and B present summary statistics for reviews of a total of 141 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.

### Panel A: Summary Statistics for Reviews of PlayStation 2 Games

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Rating</td>
<td>7.34</td>
<td>1.66</td>
<td>1.40</td>
<td>9.60</td>
</tr>
<tr>
<td>Variation of Ratings</td>
<td>0.14</td>
<td>0.13</td>
<td>0.00</td>
<td>0.68</td>
</tr>
<tr>
<td>Number of Reviews</td>
<td>9.21</td>
<td>12.43</td>
<td>1</td>
<td>63</td>
</tr>
</tbody>
</table>

### Panel B: Summary Statistics for Reviews of Xbox Games

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Rating</td>
<td>7.48</td>
<td>1.49</td>
<td>1.35</td>
<td>9.60</td>
</tr>
<tr>
<td>Variation of Ratings</td>
<td>0.17</td>
<td>0.17</td>
<td>0.00</td>
<td>0.85</td>
</tr>
<tr>
<td>Number of Reviews</td>
<td>10.30</td>
<td>16.29</td>
<td>1</td>
<td>104</td>
</tr>
</tbody>
</table>
Table 6: Measuring the Influence of Reviews on Game Demand

We use Equation (6) as the regression model. The dependent variable is $\Delta \Delta (\ln(s^j_t) - \ln(s^0_t))$. $\Delta \Delta$ indicates that we take the differences of the variable across console and over time. All regressions employ an ordinary least square specification. Heteroscedasticity-adjusted standard errors in brackets.

<table>
<thead>
<tr>
<th>Models</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \Delta$ Price</td>
<td>$-2.12^{***}$</td>
<td>$-2.07^{***}$</td>
<td>$-3.54^{**}$</td>
<td>$-2.10^{***}$</td>
<td>$-2.66^*$</td>
</tr>
<tr>
<td></td>
<td>[0.80]</td>
<td>[0.80]</td>
<td>[1.71]</td>
<td>[0.80]</td>
<td>[1.63]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Price × Popular</td>
<td>$2.94^{**}$</td>
<td>$1.43$</td>
<td>[1.38]</td>
<td>[1.48]</td>
<td>[1.80]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Price × Offline</td>
<td>$0.89$</td>
<td>$0.67$</td>
<td>[1.77]</td>
<td>[1.80]</td>
<td>[1.80]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Average Rating</td>
<td>$0.20$</td>
<td>$0.94^{**}$</td>
<td>$1.00^{**}$</td>
<td>$0.71^{**}$</td>
<td>$0.77^{***}$</td>
</tr>
<tr>
<td></td>
<td>[0.21]</td>
<td>[0.41]</td>
<td>[0.41]</td>
<td>[0.36]</td>
<td>[0.30]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Average Rating × Popular</td>
<td>$-0.71^{**}$</td>
<td>$-0.68^*$</td>
<td>$-0.64^*$</td>
<td>$-0.75^*$</td>
<td>$-0.75^*$</td>
</tr>
<tr>
<td></td>
<td>[0.36]</td>
<td>[0.39]</td>
<td>[0.39]</td>
<td>[0.39]</td>
<td>[0.39]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Average Rating × Offline</td>
<td>$-0.73^*$</td>
<td>$-0.78^{**}$</td>
<td>$-0.55$</td>
<td>$-0.61^*$</td>
<td>$-0.61^*$</td>
</tr>
<tr>
<td></td>
<td>[0.43]</td>
<td>[0.40]</td>
<td>[0.42]</td>
<td>[0.36]</td>
<td>[0.36]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Variation of Rating</td>
<td>$-0.83$</td>
<td>$-0.64$</td>
<td>[0.56]</td>
<td>[0.43]</td>
<td>[0.43]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Variation of Rating × Popular</td>
<td>$0.26$</td>
<td>$0.45$</td>
<td>[0.52]</td>
<td>[0.48]</td>
<td>[0.48]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Variation of Rating × Offline</td>
<td>$0.56$</td>
<td>$0.55$</td>
<td>[0.52]</td>
<td>[0.53]</td>
<td>[0.53]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Number of Reviews</td>
<td>$0.55^{**}$</td>
<td>$0.50^{***}$</td>
<td>[0.23]</td>
<td>[0.18]</td>
<td>[0.18]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Number of Reviews × Popular</td>
<td>$-0.11$</td>
<td>$-0.01$</td>
<td>[0.15]</td>
<td>[0.12]</td>
<td>[0.12]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Number of Reviews × Offline</td>
<td>$-0.49^{**}$</td>
<td>$-0.49^{**}$</td>
<td>[0.20]</td>
<td>[0.20]</td>
<td>[0.20]</td>
</tr>
<tr>
<td>$\Delta \Delta$ Within Group Share</td>
<td>$0.08$</td>
<td>$0.09$</td>
<td>$0.06$</td>
<td>$0.09$</td>
<td>$0.07$</td>
</tr>
<tr>
<td></td>
<td>[0.13]</td>
<td>[0.13]</td>
<td>[0.13]</td>
<td>[0.13]</td>
<td>[0.13]</td>
</tr>
<tr>
<td>Observations</td>
<td>1,142</td>
<td>1,142</td>
<td>1,142</td>
<td>1,142</td>
<td>1,142</td>
</tr>
<tr>
<td>R-square</td>
<td>0.01</td>
<td>0.01</td>
<td>0.03</td>
<td>0.01</td>
<td>0.03</td>
</tr>
</tbody>
</table>

* significant at 10%; ** significant at 5%; *** significant at 1%
Table 7: Coefficients for Different Types of Games

We use the results in Model III of Table 6 to compute the influence of review variables and price on all four types of games (e.g., popular and offline games, popular and online games, popular and offline games, and less popular and offline games). We use the linear combinations of the estimates and test them against zero to obtain these coefficients and heteroscedasticity-adjusted standard errors (in brackets).

<table>
<thead>
<tr>
<th>Price</th>
<th>Popular</th>
<th>Less Popular</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online</td>
<td>$-0.60$</td>
<td>$-3.54^{**}$</td>
</tr>
<tr>
<td></td>
<td>[1.58]</td>
<td>[1.71]</td>
</tr>
<tr>
<td>Offline</td>
<td>$-0.29$</td>
<td>$-2.65^{**}$</td>
</tr>
<tr>
<td></td>
<td>[1.05]</td>
<td>[1.11]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Average Rating</th>
<th>Popular</th>
<th>Less Popular</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online</td>
<td>$0.32$</td>
<td>$1.00^{**}$</td>
</tr>
<tr>
<td></td>
<td>[0.33]</td>
<td>[0.41]</td>
</tr>
<tr>
<td>Offline</td>
<td>$-0.45$</td>
<td>$0.22$</td>
</tr>
<tr>
<td></td>
<td>[0.32]</td>
<td>[0.25]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variation of Rating</th>
<th>Popular</th>
<th>Less Popular</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online</td>
<td>$-0.57$</td>
<td>$-0.68^*$</td>
</tr>
<tr>
<td></td>
<td>[0.43]</td>
<td>[0.39]</td>
</tr>
<tr>
<td>Offline</td>
<td>$-0.01$</td>
<td>$-0.27$</td>
</tr>
<tr>
<td></td>
<td>[0.33]</td>
<td>[0.46]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of Reviews</th>
<th>Popular</th>
<th>Less Popular</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online</td>
<td>$0.44^{**}$</td>
<td>$0.50^{**}$</td>
</tr>
<tr>
<td></td>
<td>[0.14]</td>
<td>[0.18]</td>
</tr>
<tr>
<td>Offline</td>
<td>$-0.05$</td>
<td>$0.06$</td>
</tr>
<tr>
<td></td>
<td>[0.10]</td>
<td>[0.12]</td>
</tr>
</tbody>
</table>

* significant at 10%; ** significant at 5%; *** significant at 1%
Figure 1: Conceptual Framework

- **Product Characteristics**
  - e.g., product popularity

- **Consumer Characteristics**
  - e.g., Internet experience

- **Other Factors**
  - e.g., competition, business models, design of online review systems

- **Consumers’ Reliance on Online Reviews**

- **Consumers’ Purchase Decisions**
Figure 2: 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.
Figure 3: Mean Prices, Units Sold and Ratings over Time for Games on PlayStat-
tion 2 and Xbox
X-axis is the number of months after the release of the games. The plots exclude the
observations in November and December. 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.