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

This article examines 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 article 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. The authors discuss the implications of these results in light of the increased share of niche products in recent years.

Keywords: Internet marketing, online consumer reviews, word of mouth, video game, 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 seeking to discover product quality. A recent survey by comScore (2007), an Internet marketing research company, finds that 24% of Internet users access online reviews before paying for a service delivered offline. 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; Harmon 2004).

An underlying belief behind such strategies is that online consumer reviews can significantly influence consumers' purchasing decisions. As we summarize in Table 1, several studies show that professional reviews can significantly influence consumers' decisions. With the proliferation of online review systems, many people believe that online consumer reviews are a good proxy for overall word of mouth (WOM) and can also influence consumers' decisions. Empirical findings support this idea. For example, Godes and Mayzlin (2004) find a positive relationship between online WOM and television 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, Zhang, and Awad (2007) find that adding online movie ratings to their revenue-forecasting model significantly improves the model's predictive power. In general, these studies suggest that many consumers make offline purchase decisions based on online information and that 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's (1997) study, 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 (2008) 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 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 (for a summary, see Table 2) have attempted to identify the relationship between online consumer reviews and product sales and have generated mixed

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ISSN: 0022-2429 (print), 1547-7185 (electronic)

TABLE 1
Previous Empirical Research Related to Professional Reviews

Study	Method	Data	Key Findings
Litman (1983)	Multiple regression	Movies, 1972–1978	Critics' ratings are significant factors in explaining box office revenue.
Mahajan, Muller, and Kerin (1984)	Diffusion models	Movies, 1983	Word of mouth was a significant predictor of attendance.
Wallace, Seigerman, and Holbrook (1993)	Multiple regression	Movie rental	U-shaped relationship between critic ratings and rental income.
Sawhney and Eliashberg (1996)	Forecasting model, generalized gamma	Movies, 1990–1991	Critics' reviews are positively significant for the number of adopters.
Eliashberg and Shugan (1997)	Correlation analysis	Movies, 1991–1992	Critics are predictors rather than influencer; reviews varied across critics.
Reddy, Swaminathan, and Motley (1998)	Multiple regression	Broadway shows, 1980–1982 and 1990–1994	Newspaper critics have a significant impact on the success of Broadway shows.
Holbrook (1999)	Multiple regression	Movies, pre-1986	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.
Basuroy, Chatterjee, and Ravid (2003)	Multiple regression	Movies, 1991–1993	Critics can influence and predict box office revenue.
Elberse and Eliashberg (2003)	Demand/supply model	Movies, 1999	Less positive reviews correspond to a higher number of opening screens, but more positive reviews mean more opening revenue.
Reinstein and Snyder (2005)	Differences-in-differences	Movies, early 1990s	Critics' influence on opening weekend box office revenue is smaller than previous studies would suggest but is still significant.
Zhang and Dellarocas (2006)	Multiple regression	Movies, 2003–2004	Critics' influence is more significant than previously suggested, especially on early weeks' box office revenue.
Boatwright, Kamakura, and Basuroy (2007)	Diffusion model	Movies, 1997–2001	Some critics are especially influential in affecting the box office revenue.

findings. For example, in an online experiment, Senecal and Nantel (2004) find that participants who consulted product recommendations selected these 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, Wu, and Yoon (2004) and Duan, Gu, and Whinston (2008) find that online reviews do not influence sales and serve only as predictors.

Different from these studies, which focus on the average effect of online reviews on product sales, in this article, we examine contextual factors that moderate the relationship 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 sales of more popular games. We also find that the influence of online reviews becomes greater after the early, introductory months.

Our study is the first to empirically demonstrate the differential impact of consumer reviews across products in the same product category. The results imply 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 through online channels should be more concerned about online consumer reviews and manipulations of online review systems because online reviews could significantly affect their sales. Because the proliferation of online markets has led to the emergence of many niche producers, a phenomenon often dubbed the

TABLE 2
Previous Empirical Research Related to Consumer Reviews

Study	Method	Data	Key Findings
Resnick and Zeckhauser (2002)	Multiple regression	eBay, 1999	Sellers with better reputations are more likely to sell their items but they enjoy no boost in price.
Godes and Mayzlin (2004)	Multiple regression	Television shows, 1999–2000	Online conversations offer one way to measure word of mouth.
Chen, Wu, and Yoon (2004)	Multiple regression	Amazon.com books, 2003	Consumer ratings are not correlated with sales.
Senecal and Nantel (2004)	Generalized estimating equations	Online experiment	Participants who consulted product recommendations selected recommended products twice as often as those who did not consult recommendations.
Liu (2006)	Multiple regression	Movies, 2002	WOM information offers significant explanatory power for both aggregate and weekly box office revenue, especially in the early weeks after a movie opens.
Chevalier and Mayzlin (2006)	Differences-in-differences	Books, 2003–2004	Online amateur book ratings affect consumer purchasing behavior.
Dellarocas, Zhang, and Awad (2007)	Diffusion model	Movies, 2002	Online amateur movie ratings can be used as a proxy for word of mouth.
Duan, Gu, and Whinston (2008)	Simultaneous system	Movies, 2003–2004	The rating of online user reviews has no significant impact on movies' box office revenues.

"long tail" (Anderson 2006), our results have important implications for their survival.

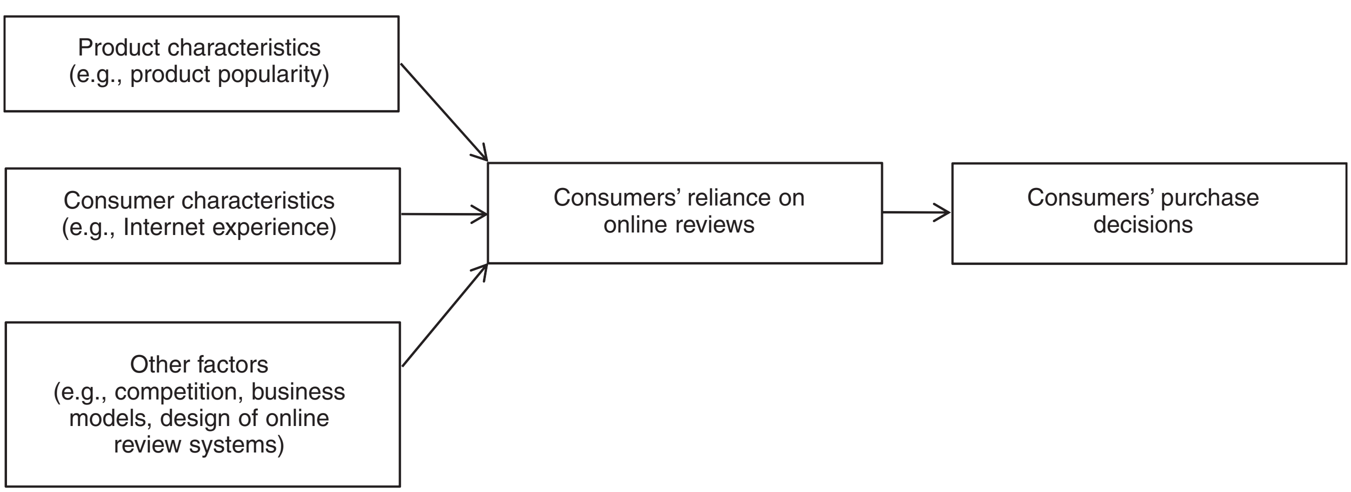
In the following sections, we develop our conceptual framework and provide background information about the video game industry and the cross-platform development of video games. After discussing the data sources, we develop an empirical strategy and present the results. We conclude with a discussion of the implications of our findings.

Conceptual Framework

We focus on single-purchase products in our study. Information goods, such as books, movies, music, and 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. Thus, online reviews 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. In turn, the degree of reliance depends on product- and consumer-specific characteristics. In addition, other factors, such as competition, business models (e.g., business-to-consumer, consumer-to-consumer), or even the online review system's design (e.g., how ratings are displayed, how easy it is to rate an item), may affect consumers' reliance on reviews.

The framework is closely related to the psychological choice model in Hansen (1976), in which the effectiveness

FIGURE 1
Conceptual Framework



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 genres such as action movies and comedies. Cheema and Papatla (2010) 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 reliance on certain information sources. For example, Westbrook and Fornell (1979) show that consumers' background characteristics, such as education attainment, 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 relationship 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, p. E1) explains, a consumer "may not trust just one nonexpert,... but if 9 out of 10 nonexperts agree, it's probably worth buying." Chen, Wu, and Yoon (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 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 difficult 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 (Bornstein 1989; Zajonc 1980). Along this line, Janiszewski (1993) finds that the mere exposure effect persists even when initial exposure to brand names and product packages is unintended. Because popular products are discussed more frequently than less popular products, and thus consumers are exposed to them repeatedly, the exposure effect could have a significant impact on consumer purchasing behavior.

The preceding discussion suggests that both the ratings and the number of reviews could be more salient for popular products. Because we measure product popularity by its sales, we hypothesize the following:

> H_{1a}: An increase in online reviews (e.g., online ratings, the number of online reviews) results in higher incremental sales for products that currently have relatively high sales.

Conversely, online consumer reviews could be less influential for popular products. For example, consumers may have a lower need to resort to online reviews for popular products. A major reason consumers use online reviews is to obtain quality information to reduce risk (Bolton, Katok, and Ockenfels 2004; Chen, Xu, and Whinston 2009; Clemons, Gao, and Hitt 2006; Forsythe and Shi 2003; Pavlou and Gefen 2004). Being popular in itself signals higher quality. Previous studies have shown 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 influences perceived quality, such as signaling, creation of network externalities, and inclusion as an attribute in consumers' quality functions.

Studies have also shown that the purchase of popular products tends to minimize potential risk. DeSarbo and colleagues (2002) argue that consumers prefer popular products because popularity represents 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 to follow the crowd (e.g., Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992). The literature on consumer decision making (e.g., Josephs et al. 1992; Zeelenberga and Beattieb 1997; Zeelenberga, Van der Pligta, and De Vriesa 1996) 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. Thus, consumers interested in a less popular product are likely to search and access more WOM information to shield themselves from possible regret (Chatterjee 2001).

Finally, consumers use a mix of online (e.g., online reviews, blogs) and offline (e.g., family and friends, salespeople, magazines) WOM information to help structure their decisions. Prior research has shown that WOM effectiveness depends on the strength of ties or the intensity of the relationship among consumers (e.g., Granovetter 1973). Strong ties are perceived as more influential than weak ties, and they are more likely to be used as sources of information (e.g., Bansal and Voyer 2000; Brown and Reingen 1987). Because consumers often cannot determine the source's credibility in an online environment, tie strength online is typically weak (e.g., Chatterjee 2001; Mesch and Talmud 2006). Indeed, experimental evidence shows that when both channels are present, the offline channel is generally preferred over the online channel (Frambach, Roest, and Krishnan 2007). Because 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 thus are less likely to be influenced by online reviews.

The foregoing discussion 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 postpurchase regret, and such quality information is likely to be unavailable from offline channels. Therefore, it is an empirical question whether online reviews are more influential for popular or less popular products. We propose the following competing hypothesis:

> H_{1b}: An increase in online reviews (e.g., online ratings, the number of online reviews) results in higher incremental sales for products that currently have relatively low sales.

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., Lazonder, Biemans, and Wopereis 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 are 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 from that of 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. Therefore, Internet experience may moderate the evaluation of online information.

Thus, because 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 hypothesize the following:

> H_{2a}: An increase in online reviews (e.g., online ratings, the number of online reviews) results in higher incremental sales 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. Because 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 (Cheema and Papatla 2010). 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 (2010) 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. However, assessing the validity of these information sources 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 relationship 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 the following:

> H_{2b}: An increase in online reviews (e.g., online ratings, the number of online reviews) results in higher incremental sales for products targeting consumers with less Internet experience.

In the context of video games, because games have different genres and story lines, they may or may not offer an online multiplayer 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 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 a relatively high level of skill in coordinating and communicating online with other players in real time. Thus, we expect that, on average, consumers purchasing online games will 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, Wang, and Fang 2005).

Therefore, we 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, and its growth far outpaces other entertainment industries, such as movies and music. From 2003 to 2006, the video game software industry's annual growth rate exceeded 17%, in contrast to the U.S. economy's 2% growth rate over the same period (The Entertainment Software Association 2007). The industry's annual revenue was approximately $17.94 billion in 2007 (Thorsen 2008), 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). The penetration rate of video game consoles is also high: Approximately 41% of U.S. households owned video game consoles in 2006 (Arendt 2007). Thus, our study 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 gave out 1563 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 (hereinafter, NPD), the average selling price of a game was $38.36 at the end of 2007. Because most gamers are young and have limited incomes, they frequently use reviews to avoid bad purchases (Bounie et al. 2005). Therefore, it is 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 cost of developing a contemporary video game is approximately $6–$10 million (*Edge* 2005). 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 need to rewrite the entire game. Development teams would use assembly language, a human-readable notation for the machine language, to write most games because this language optimized the processing speed and required little overhead. Today, because 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 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 view 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 the ages of 18 and 34, positioning themselves directly against each other; therefore, we expect the two gaming populations to be similar. 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.

Empirical Analysis

Data

Data on console sales and game sales come from NPD, a leading market research firm that tracks this industry. NPD collects data from approximately 17 leading 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 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.

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 United States and the most popular one for video games, reaching more than 10 million unique gamers each month (GameZone 2004). 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 they ship to retail channels. In March 2003, GameSpot began 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 log-in 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 (game play, graphics, sound, value, and reviewer's tilt), reviewers use a scale ranging from 1 to 10 for their reviews, 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 vary both across consoles and over time and are the focus of our analysis. Even for the same game titles, player reviews tend to be different across consoles.

We collect reviews for each game in each month between March 2003 and October 2005. Following previous research on consumer reviews (e.g., Chevalier and Mayzlin 2006; Zhang and Dellarocas 2006), we focus on three review variables: the average rating, the coefficient of variation of ratings, and the total number of reviews posted. 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. Prior research has shown that for different products, variation of consumer reviews may be positively or negatively associated with product sales (e.g., Martin, Barron, and Norton 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 a 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 can also obtain review information from other channels, such as online bulletin boards and chat rooms. Therefore, our current estimate might 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.

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. Because 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 between reviews and product sales might 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 unobserved 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 on different dates and use a differences-in-differences approach to eliminate book- and site-specific effects.

In this article, similar to Chevalier and Mayzlin (2006), we adopt a differences-in-differences approach. The differences-in-differences approach is widely used to circumvent many of the endogeneity problems that typically arise when making causal arguments (Meyer 1995). Our empirical analysis hinges on the video games that are released for two 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, which 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 an increase in the game title's sales on one console relative to the same game title's sales on the other console is a result of differences in reviews. As with other studies using the differences-in-differences approach, the key underlying assumption here is that the effect of these unobserved console-specific factors is the same for games on both consoles in each period.

Our analysis differs from that of Chevalier and Mayzlin (2006) in several aspects. First, the two studies focus on different questions. Chevalier and Mayzlin examine 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, the demand for individual books is implicitly assumed to be independent of that of competitors, though in reality, the availability of books in the same category is likely to affect the demand for a particular book. Third, our sales data for games cover the whole U.S. market, while Chevalier and Mayzlin examine book sales only on two Web sites and approximate book sales using ranks. Thus, our results 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 the book data that Chevalier and Mayzlin use 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 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 decides whether to purchase a game. In the second stage, if the player chooses to purchase a game, he or she then decides which game to purchase. For any given game, the player 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^k_{ijt}, 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 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 intertemporal 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 approximately 33 months, but on average, more than 50% of game sales occur within the first four months after a game's release. Therefore, for any game, the first four months after release could be considered the period in which it is popular. 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. Thus, we express the player's utility, u^k_{ijt}, as a function of price (p^k_{jt}), lagged review variable ($r^k_{j,t-1}$), a dummy indicating whether a game is popular (popular_{jt}), a dummy indicating whether a game can only be played offline (offline_j), and other game characteristics (ξ^k_{jt}):

$$(1)\quad u^k_{ijt} = \beta_0 + \beta_1 p^k_{jt} + \beta_2 r^k_{j,t-1} + \beta_3\left(r^k_{j,t-1} \times \text{popular}_{jt}\right) + \beta_4\left(r^k_{j,t-1} \times \text{offline}_j\right) + \beta_5 \text{popular}_{jt} + \beta_6 \text{offline}_j + \xi^k_{jt} + \zeta^k_{jgt} + (1-\sigma)v^k_{ijt}.$$

The two dummy variables, popular_{jt} and offline_j, indicate different subgroups among all the video games. Because 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 can measure the effects of online reviews of different types of products (Aiken and West 1991). For example, β_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 $\beta_2 + \beta_3 + \beta_4$ measure 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, ζ^k_{jgt} and v^k_{ijt}, where ζ^k_{jgt} represents player utility common to all games of group g and v^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. When $\sigma \to 1$, 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 Equation 1 for two 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 subsequently. Therefore, we could use straightforward instrumental variable methods to handle endogenous variables, such as game prices (Berry 1994).

We normalize the utility from the outside good to be zero. Because game players must 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. In addition, because the two consoles are incompatible, 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 $s^k_{jt|g}$. Thus, $s^k_{jt|g}$ can be computed as $s^k_{jt}/(1 - s^k_{0t})$, where s^k_{0t} is the market share of the outside option in period t for console k. Following Berry (1994) and Cardell (1997), we derive the demand equation for the two-stage nested logit model as follows:

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

Given the panel structure of data, we decompose the component ξ^k_{jt} as follows:

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

where θ_{jt} is a game-specific component that is the same for the same game across different platforms but can vary over time, η^k_j is the console-specific effect, and ε^k_{jt} is an i.i.d. normal error term varying across games and over time. The θ_{jt} component is related to factors such as promotions by game publishers, the brands of the game publishers, and the game's age and quality, and η^k_j 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, η^k_j 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 the following:

$$(3)\quad \ln\left(s^p_{jt}\right) - \ln\left(s^p_{0t}\right) = \beta_0 + \beta_1 p^p_{jt} + \beta_2 r^p_{j,t-1} + \beta_3\left(r^p_{j,t-1} \times \text{popular}_{jt}\right) + \beta_4\left(r^p_{j,t-1} \times \text{offline}_j\right) + \beta_5 \text{popular}_{jt} + \beta_6 \text{offline}_j + \sigma \ln\left(s^p_{jt|g}\right) + \theta_{jt} + \eta^p_j + \varepsilon^p_{jt}, \text{ and}$$

$$(4)\quad \ln\left(s^x_{jt}\right) - \ln\left(s^x_{0t}\right) = \beta_0 + \beta_1 p^x_{jt} + \beta_2 r^x_{j,t-1} + \beta_3\left(r^x_{j,t-1} \times \text{popular}_{jt}\right) + \beta_4\left(r^x_{j,t-1} \times \text{offline}_j\right) + \beta_5 \text{popular}_{jt} + \beta_6 \text{offline}_j + \sigma \ln\left(s^x_{jt|g}\right) + \theta_{jt} + \eta^x_j + \varepsilon^x_{jt}.$$

The within-group market shares (WGSs), $\ln(s^p_{jt|g})$ and $\ln(s^x_{jt|g})$, are, by definition, endogenous and require instrumental variables. Following Einav (2007), we use the number of games available for each console at time t as the instrument for the WGS. A large number of games implies intense competition and therefore should be negatively associated with the WGS. In addition, because 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. Furthermore, game prices, p^p_{jt} and p^x_{jt}, could be endogenous in our demand model. Although we do not have cost-side variables to use as instruments, as Berry (1994) and Nair, Chintagunta, and Dubé (2004) suggest, we could use characteristics of competing games as instruments. For each game, we collected data on its genre (e.g., first-person shooter, party games, puzzle games) and the Entertainment Software Rating Board rating (e.g., everyone, adult-only, teen). Following Nair, Chintagunta, and Dubé's approach, we use the number and average age of competing games in the same genre, of competing games in the same Entertainment Software Rating Board group, and of all competing games, as well as their squared terms, as instruments for game prices in each month.

The parameter θ_{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. Because θ_{jt} is the same across console systems, we eliminate the game-specific effects by differencing the data across consoles:

$$\text{(5)} \quad \Delta M_{j,t} = \beta_1 \Delta p_{j,t} + \beta_2 \Delta r_{j,t-1} + \beta_3\left(\Delta r_{j,t-1} \times \text{popular}_{jt}\right) + \beta_4\left(\Delta r_{j,t-1} \times \text{offline}_j\right) + \sigma \Delta WGS_{j,t} + \Delta\eta_j + \varepsilon_{j,t},$$

where

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

The variable $\Delta\eta_j$, which captures the differences in console-specific effects, is also unobserved but does not vary over time. Because console differences may affect differences in game prices and reviews, we take an additional difference of Equation 5 between period t and t + 1 and obtain the following:

$$\text{(6)} \quad \Delta\Delta M_{j,t} = \beta_1\left(\Delta\Delta p_{j,t}\right) + \beta_2\left(\Delta\Delta r_{j,t-1}\right) + \beta_3\left(\Delta\Delta p_{j,t} \times \text{popular}_{jt}\right) + \beta_4\left(\Delta\Delta p_{j,t} \times \text{offline}_j\right) + \sigma\left(\Delta\Delta WGS_{j,t}\right) + \varepsilon_{j,t}.$$

Equation 6 is 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. Because the two consoles are incompatible with each other and most game players only own one console 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. Thus, our empirical study serves as a test for this assumption.

Summary Statistics

Our final data set consists of 220 game titles that were available for the two consoles between March 2003 and October 2005. Of these, 79 had different release dates for the two consoles, and we remove them 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). However, consumers' purchase frequency 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: The average monthly units sold are close to 20 million between January and October, but this number increases substantially for November and December. Thus, consumers are more likely to purchase multiple games in November and December. We remove observations in November and December from our data set.[1]

[1]Several recent articles (e.g., Dubé 2004; Hendel 1999; Hendel and Nevo 2006) present techniques that can accommodate multiple discrete choices. Because these models in general do not yield linear specifications, it is difficult to combine them with our differences-in-differences approach.

FIGURE 2
Mean Units and Mean Revenue by Month for All Games

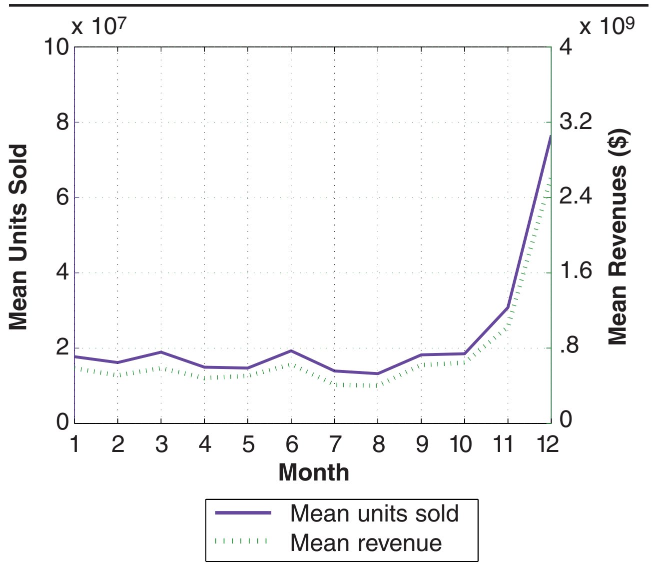


Table 3 provides summary statistics for games in our sample. A t-test indicates that the monthly unit sales of games for PlayStation 2 are significantly greater than those for Xbox. The result is consistent with the larger installed base of PlayStation 2 console and the strong indirect network effects that Clements and Ohashi (2005) and Zhu and Iansiti (2009) document. 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 PlayStation 2 console have positive sales.

Table 4 presents summary statistics of reviews as of October 2005. The data suggest that reviews are overwhelmingly positive for games for both consoles. Researchers have observed similar patterns in other contexts, such as book reviews on Amazon.com (Chevalier and Mayzlin 2006) and reputation profiles on eBay (Resnick and Zeckhauser 2002). On average, there are 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 similar. A concern is that the same reviews may be posted for both consoles, and as a result, reviews from the two gaming populations are artificially similar. We check this possibility and find that only 3.3% of the reviewers write reviews for both consoles.

Figure 3 shows the mean prices, units sold, and ratings for PlayStation 2 and Xbox games. In all three panels, the patterns for PlayStation 2 and Xbox are similar. Both average price and average units sold decline over time. The average price declines almost linearly during the first ten months, and the average units sold also drops significantly for the first few months. Because 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. 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 that reported by Dellarocas, Zhang, and Awad (2007) and Li and Hitt (2008). The variance of the mean ratings increases over time because we have fewer reviews for old games.

TABLE 4
Summary Statistics for Reviews

A: Summary Statistics for Reviews of PlayStation 2 Games

Variable	M	SD	Minimum	Maximum
Average rating	7.34	1.66	1.40	9.60
Variation of ratings	.14	.13	.00	.68
Number of reviews	9.21	12.43	1.00	63.00

B: Summary Statistics for Reviews of Xbox Games

Variable	M	SD	Minimum	Maximum
Average rating	7.48	1.49	1.35	9.60
Variation of ratings	.17	.17	.00	.85
Number of reviews	10.30	16.29	1.00	104.00

Notes: Panels 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. We measured the variation of ratings 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.

Regression Results

Table 5 presents the regression results based on the differences-in-differences specification in Equation 6. We use the differences of $\ln(s_{jt}^k) - \ln(s_{0t}^k)$ across consoles and over time as the dependent variables in all models. In Model 1, we use the differences-in-differences measures of price, average rating of the reviews, and WGS of the games.[2] We find that game price negatively affects game demand, while average consumer rating has no effect on it. The small and nonsignificant coefficient of the WGS suggests that video games are poor substitutes for each other, which is consistent with Nair's (2007) finding.

In Model 2, 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, popular_{jt}, as a dummy variable, which takes the value of 1 if the sales of game j for both consoles are greater

[2]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.

TABLE 3
Summary Statistics for Games

A: Summary Statistics for Games on PlayStation 2

Variable	Number of Observations	M	SD	Minimum	Maximum
Monthly sales (units)	3,330	10,038.84	25,518.40	5	561,540
Monthly price ($)	3,330	21.58	11.23	1.80	54.85

B: Summary Statistics for Games on Xbox

Variable	Number of Observations	M	SD	Minimum	Maximum
Monthly sales (units)	3,305	5,499.10	15,816.72	7	378,194
Monthly price ($)	3,305	21.32	11.10	1.88	54.79

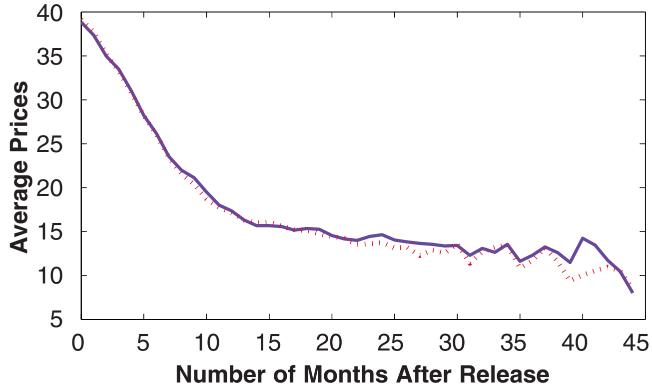
Notes: Panels A and B present summary statistics for games developed on both PlayStation 2 and Xbox consoles in our sample. The period is from March 2003 to October 2005. We calculate the monthly price calculated by dividing the monthly dollar value of sales by the volume of units sold.

than the mean performance of all games in month t. Information on each game's online capability is collected from GameSpot. GameSpot specifies whether a game has an online play mode. We also verify our data with information from game publishers' and console manufacturers' Web sites.[3] 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.

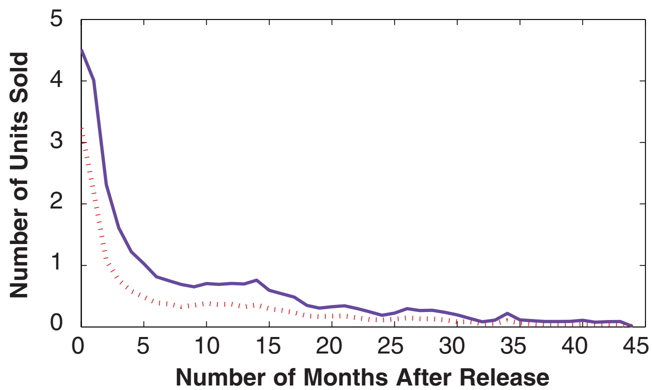
In Model 3, we add the differences-in-differences measures of other review variables, such as the variation of the

FIGURE 3
Mean Prices, Units Sold, and Ratings over Time for Games on PlayStation 2 and Xbox

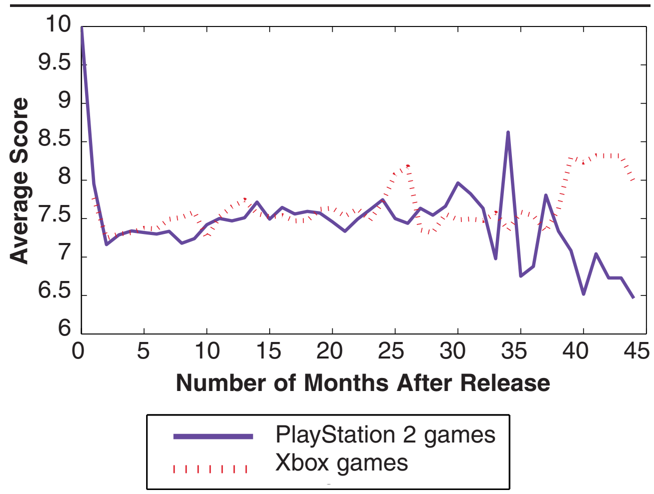
A: Average Prices



B: Number of Units Sold



C: Average Score



Notes: The plots exclude the observations in November and December. Because 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.

[3]On a more technical note, online play requires online platforms (often provided by either console manufacturers or game publishers). Because online platforms designed for one console may not be usable 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 (it is often included in the game descriptions). Even if the online capability of a game is not supported at the time of purchase, players often anticipate that they will be able to play it online in the near future. Thus, we define online games or offline games on the basis of their online capability (instead of whether the games are actually being played online).

TABLE 5
Measuring the Influence of Reviews on Game Demand

	Models				
	1	2	3	4	5
ΔΔ Price	–2.12***	–2.07***	–3.54**	–2.10***	–2.66*
	(.80)	(.80)	(1.71)	(.80)	(1.63)
ΔΔ Average rating	.20	.94**	1.00**	.71**	.77**
	(.21)	(.41)	(.41)	(.36)	(.30)
ΔΔ Within-group share	.08	.09	.06	.09	.07
	(.13)	(.13)	(.13)	(.13)	(.13)
ΔΔ Average rating × popular		–.71**	–.68*	–.64*	–.75*
		(.36)	(.39)	(.39)	(.39)
ΔΔ Average rating × offline		–.73*	–.78**	–.55	–.61*
		(.43)	(.40)	(.42)	(.36)
ΔΔ Price × popular			2.94**		1.43
			(1.38)		(1.48)
ΔΔ Price × offline			.89		.67
			(1.77)		(1.80)
ΔΔ Variation of rating			–.83		–.64
			(.56)		(.43)
ΔΔ Variation of rating × popular			.26		.45
			(.52)		(.48)
ΔΔ Variation of rating × offline			.56		.55
			(.52)		(.53)
ΔΔ Number of reviews			.55**		.50***
			(.23)		(.18)
ΔΔ Number of reviews × popular			–.11		–.01
			(.15)		(.12)
ΔΔ Number of reviews × offline			–.49**		–.49**
			(.20)		(.20)
Observations	1142	1142	1142	1142	1142
R^2	.01	.01	.03	.01	.03

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: We use Equation 6 as the regression model. 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. ΔΔ indicates that we take the differences of the variable across console and over time. All regressions employ an ordinary least square specification. Heteroskedasticity-adjusted standard errors are in parentheses.

ratings and the number of reviews, and their interactions with game popularity and online capability. Because 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 2. In addition, we find that the number of reviews has a positive effect on less popular and online games. A possible explanation for this is that having a large number of reviews signals a game's popularity. This result is also likely caused by the presence of direct network effects: For games that can be played online, players are more likely to purchase games that many others have bought. The effect of the number of reviews becomes weaker for offline games.

In Models 4 and 5, we employ an intertemporal 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 popular if it is less than four months old and less popular otherwise. We replicate the analyses in Models 2 and 3 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 noteworthy in light of prior research suggesting that product promotions are more effective in the early stages of a product's life cycle because 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. A 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. We also note that R-squares of our models are relatively small. A possible reason for this is that the variance of the error term in our empirical specification could be large because we obtained the error term after differencing four error terms in our differences-in-differences approach.

The coefficients of the price variable and the review variables in Table 5 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, less popular and offline games). Table 6 summarizes the results (based on Model 3 in Table 5). 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 previous studies because most of these studies only consider one or two aspects of online reviews. For example, Chen, Wu, and Yoon (2004) and Duan, Gu, and Whinston (2008) 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, Gu, and Whinston 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}.

TABLE 6
Coefficients for Different Types of Games

	Popular	Less Popular
Price		
Online	–.60	–3.54**
	(1.58)	(1.71)
Offline	–.29	–2.65**
	(1.05)	(1.11)
Average Rating		
Online	.32	1.00*
	(.33)	(.41)
Offline	–.45	.22
	(.32)	(.25)
Variation of Rating		
Online	–.57	–.68*
	(.43)	(.39)
Offline	–.01	–.27
	(.33)	(.46)
Number of Reviews		
Online	.44***	.50***
	(.14)	(.18)
Offline	–.05	.06
	(.10)	(.12)

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: We use the results in Model 3 of Table 5 to compute the influence of review variables and price on all four types of games (i.e., popular and offline games, popular and online games, less popular and offline games, and less popular and online games). We use the linear combinations of the estimates and test them against zero to obtain these coefficients and heteroskedasticity-adjusted standard errors (in parentheses).

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. Thus, firms' online marketing strategies need to adjust accordingly.

The finding that online reviews are more influential for less popular games suggests that the informational role of reviews becomes more salient in an environment in which 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. Because of the scarcity of available information about niche products, even one negative review can be detrimental. Superior online WOM translates more easily into sales for niche products, and thus 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, Hu, and Simester 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, Hu, and Smith (2006) find that obscure book titles, which are typically not available in conventional bookstores, account for approximately 40% of Amazon.com's book sales in 2000. Although 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, though the number of video titles selling only a few copies every week increases almost twofold during this period, the number of nonselling titles rises rapidly and becomes four times as high as in 2000. Because 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. Therefore, it is crucial for niche product producers to devote their marketing efforts to online review systems when they take advantage of online channels to sell their products.

This study also finds evidence to support the notion that online reviews are more influential when consumers have relatively greater Internet experience. Echoing the discussion in the conceptual framework about users' Internet experience, the 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 (Cheema and Papatla 2010; Klein and Ford 2003). As the Internet population continues to grow, consumers will 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.com has recently modified the way it reports star levels for items. While previously it showed only an average star rating, it now shows how many people rated the item with each of the 1–5 stars; readers can choose to read reviews for a given star level.

Research Implications

This research provides a potential positive reconciliation of the mixed results from previous studies. For example, Chevalier and Mayzlin (2006) examine book sales at Amazon.com and find that online reviews influence book sales, but, using a similar data set from Amazon.com, Chen, Wu, and Yoon (2004) 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, Gu, and Whinston (2008) find the opposite. Researchers have not been able to reconcile the stark differences in results and instead have attributed them to methodological shortcomings. For example, Duan, Gu, and Whinston point out that the mixed finding could be the result of researchers conducting their analyses in a cross-sectional context and not controlling 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 nontechnical books may find that online reviews play different roles.

This work could be extended in several directions. First, further research could take a similar approach to examine the differential roles of critics' 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 at the box office. However, several recent studies (e.g., Basuroy, Chatterjee, and Ravid 2003; Reinstein and Snyder 2005) find that film critics can influence opening weekend box office revenues. Heterogeneity across different movies might be a source of these divergent findings.

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

Third, further research could investigate firms' online and offline marketing strategies and compare their effectiveness. Our research indicates that promotions in the offline channel may reduce the efficacy of online reviews. Thus, it would be worthwhile to theoretically and empirically analyze firms' optimal strategy in allocating marketing resources to online and offline channels.

Finally, further 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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