The Development and Impact of Consumer Word of Mouth in New Product Diffusion

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This Draft: August 2009

Key words: word of mouth; learning models; durable goods diffusion; advertising; publicity; video games

The authors would like to express their gratitude to Nielsen Online for sharing with us the database on consumer word of mouth used in this study. Thomas Bao and Lily Hou offered excellent research assistance. We also benefited from comments by seminar participants at Tuck School of Business at Dartmouth.

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Abstract

We investigate how consumer word of mouth (WOM) develops over time and in turn influences new product adoption. We develop a dynamic aggregate-level model of WOM development and new product diffusion that explicitly captures consumers' learning of product quality from both marketing communications and WOM. It allows us to measure how effectively firms' marketing efforts generate WOM (*buzz*) and to determine whether WOM influences product adoption primarily through an *informative* role (i.e., helping the consumer learn product quality) or a *persuasive* role (i.e., exerting a direct impact on sales, for example, by increasing awareness). A formal treatment of the endogeneity issue inherent in the WOM-sales relationship enables us to infer short-term and long-term sales elasticity of WOM. The model is estimated using simulated generalized method of moments (GMM) and applied to the U.S. video game market.

Our results indicate: (1) media publicity is especially effective at generating WOM for video games while media advertising is ineffective. (2) WOM is the key source of quality learning. It has a larger informative effect than publicity and advertising combined. (3) While WOM also has a significant persuasive effect, the informative effect dominates; therefore, buzz marketing is economically meaningful only for high-quality products.

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1. Introduction

Marketing scholars and practitioners have long realized the role of consumer word of mouth (WOM) in the success or failure of a new product. In recent years, a flourish of online social media and user generated content (UGC) has enabled consumers to easily publish and receive information and opinions about new products. This in turn both necessitates and enables marketers to analyze the impact of WOM, as well as attempt to influence WOM in a way that facilitates new product adoption.

We present a conceptual structure for assessing this process in Figure 1. The figure first shows that firms' marketing communications such as advertising and media publicity may generate WOM. We refer to this as the "*buzz effect*". While an increasing number of marketers believe they can seed and motivate WOM through these traditional marketing communication tools, there is little empirical evidence on the presence and magnitude of this effect.

[Figure 1 Goes Here]

Figure 1 next shows how WOM may influence new product adoption. Researchers have proposed that marketing communication influences consumer choice either by providing diagnostic information about product quality (the *informative effect*), or by increasing product awareness or salience (the *persuasive effect*). While previous research has investigated these roles for media advertising and personal selling (e.g., Erdem and Keane 1996; Narayanan, Manchanda, and Chintagunta 2005), no studies have examined them for WOM. However, this distinction has important ramifications for the design of buzz marketing programs. If the informative effect dominates, then higher-quality products benefit more from WOM, and marketers of high quality products should design buzz marketing programs to emphasize quality (e.g., by sending samples to popular bloggers). If the persuasive effect dominates, then the goal of buzz marketing is just to "get out the news": both higher- and lower-quality products would benefit from such programs (e.g., humorous viral videos with minimal product information).

Figure 1 serves an important purpose in identifying three mechanisms – the buzz effect, informative effect, and persuasive effect – that generate WOM and translate it into product adoption. However, it is but a snapshot of what is inherently a dynamic process: Initial WOM can precipitate future WOM; consumers' current perceptions of product quality provide the "prior" for future perceptions; furthermore, higher sales levels may lead to higher levels of consumer WOM, which in turn gives impetus to future WOM and product adoption. Therefore, to fully measure the drivers and effects of WOM, one has to consider the dynamics by which WOM, quality perceptions, and product adoption move together.

Our purpose, therefore, is to examine the development and impact of WOM by measuring the buzz, informative, and persuasive effects, and the dynamics of how these mechanisms play out over time. To address these issues, we propose a dynamic aggregate-level model of WOM development and new product diffusion. The model consists of a WOM equation to measure buzz effects, a Bayesian learning model of product quality to capture the informative effect of WOM and marketing communication, and a sales equation that translates quality perceptions along with t persuasive effects into product adoption. These models are all dynamic and feed on each other over time.

Methodologically, our model contributes to the WOM literature by rigorously addressing endogeneity problems that make it difficult to establish the causal link between WOM and sales as opposed to only an associative relationship (e.g., Godes and Mayzlin 2004; Liu 2006). Our model takes three steps in this regard. First, we model WOM and marketing communication in an integrated framework; in particularly, the model allows WOM to be influenced by marketing efforts. Van den Bulte and Lilien (2001) showed that the inferred social contagion effect could be a mere artifact for omitted marketing variables. Since both WOM and sales are supposedly influenced by marketing, not controlling for marketing activities could result in an overestimation of the WOM effect. Second, we control for consumers' perception of product quality through the Bayesian learning model. Since product quality tends to drive both WOM and sales, not controlling for product quality may also produce a spurious relationship. Third, even after marketing efforts and product quality are accounted for, there may still be unobserved factors correlated with the drivers of both WOM and sales (e.g., a video game is based on a newly released blockbuster movie). We construct a GMM estimator with instrumental variables to correct for possible correlation between the error term and endogenous regressors.

We apply the model to the U.S. video game software market during 2007-2008. Our WOM measures come from a unique dataset that encompasses the majority of consumers' online discussions of video games. The results suggest: (1) *Buzz Effect:* Product publicity plays a crucial role in stimulating consumer WOM while media advertising has no significant buzz effect. (2) *Informative Effect:* WOM is the dominant source through which consumers learn about product quality, accounting for about 80% of quality learning while publicity accounts for the remaining 20% for an average video game. Advertising has a significant informative effect only for the subgroup of products that are major innovations, although WOM still dominates for these products. (3) *Persuasive Effect:* Publicity, WOM, and media advertising all have persuasive effects, in decreasing order of magnitude. (4) *Total WOM Impact:* When dynamics are taken into account, the long-term elasticity of new product sales with respect to WOM is 0.15 for an average video game in our sample, but it hinges on product quality: WOM elasticity ranges from 0.40 for the top quality tier to 0.02 for the bottom quality tier, implying that a buzz marketing program is most effective when for high-quality products. We discuss the managerial implications of the empirical results for managers involved in marketing new products.

The rest of the article is organized as follows: In Section 2, we review three streams of extant literature pertaining to the current work. Section 3 introduces the econometric model. Section 4 describes the data and discusses the estimation approach, Section 5 reports results from the empirical study, and Section 6 discusses the managerial implications. Section 7 concludes.

2. Related Literature

An emerging literature in marketing has sought to measure consumer WOM and quantify its effect on product performance (e.g., Godes and Mayzlin 2004; Chevalier and Mayzlin 2006; Liu 2006). Three important issues remain unresolved in this literature. First, how does consumer WOM evolve over time? Specifically, to what extent do firms' own marketing communications such as advertising and publicity seed and facilitate WOM? Second, what is the mechanism through which WOM influences new product sales? Does it primarily play an informative role (through educating consumers about the quality of a new product) or a persuasive role (through increasing product awareness and salience)? Third, due to the endogeneity issue discussed in the previous section, it is challenging to quantify the marginal contribution of WOM to sales, compared to only establishing an associative or predictive relationship between the two.[1] By

[1] An exception is a "differences in differences" approach proposed by Chevalier and Mayzlin (2006). By examining whether a temporal change in the number and valence of consumer reviews at Amazon.com relative to BarnesandNoble.com predicts a change in the relative sales at the two retailers, this approach neatly controls for unobserved book attributes that affect both consumer reviews and sales. However, it is hard to implement this approach on other forms of consumer generated content than product reviews on retailers' websites.

addressing these three important issues, our current work contributes to the extant WOM literature both substantively and methodologically.

A substantial literature has investigated the role of learning in consumer choice in the presence of uncertainty about product quality. In these models, consumers learn about quality through their own consumption experiences (for repeat-purchased products) or firms' marketing activities (e.g., advertising) and update prior quality beliefs in a Bayesian manner (e.g., Erdem and Keane 1996; Narayanan, Manchanda, and Chintagunta 2005; Iyengar, Ansari, and Gupta 2007; Mehta, Chen, and Narasimhan 2008). However, despite the important role of WOM in consumers' learning process, with the exception of Erdem et al. (2005), none of the extant studies have examined the informative role of WOM. Our work differs from Erdem et al. in that, while they treated WOM as an exogenous information source, we model WOM as an endogenous outcome of both firms' marketing efforts and of previous adoption.

Our paper is also related to research aimed at quantifying the informative vs. persuasive effects of marketing communications (Erdem and Keane 1996; Ackerberg 2001; Narayanan, Manchanda, and Chintagunta 2005; Ching and Ishihara 2008) [2]. The relative importance of these two effects has important managerial implications. For instance, Narayanan et al. found that detailing in the pharmaceutical industry has a predominantly informative effect in the introductory stage of a drug while the persuasive effect dominates later in its lifecycle. Combining marketing communications and consumer WOM in an integrated framework as shown in Figure 1, we contribute to this literature in two aspects. First, we quantify and compare the informative/persuasive roles of marketing communication vs. WOM in the new product diffusion process. Second, we measure the *buzz effect*, i.e., the ability of marketing communication to generate consumer WOM.

3. Model

We propose a dynamic aggregate-level model of WOM development and durable goods diffusion that explicitly accounts for consumers' learning about the quality of a new product from both marketing communications and WOM. As reported earlier, our model has three main

[2] This effect is variably termed as "prestige effect" (e.g., Ackerberg 2001), "direct (goodwill) effect" (Narayanan, Manchanda, and Chintagunta 2005), "persuasive effect" (Ching and Ishihara 2008) . In addition to the informative and prestige effects, past research also proposed a third effect that captures the interaction of marketing communication and consumption experience on consumer choice (e.g., Mehta, Chen, and Narasimhan 2008). Since this only applies to repeat-purchased nondurable goods, we do not consider it in the current study.

components: (1) the WOM generation process,; (2) a durable goods diffusion model of new product adoption; (3) the learning process by which consumers learn the quality of the new product. These three ingredients form a dynamic system that enables marketers to gauge the short-term and long-term effects of WOM and other marketing communications, particularly media advertising and publicity. Since we estimate the model on discrete-time (i.e., monthly) data, we have to make certain assumptions about the timing of events during a time interval. Figure 2 graphs the sequence of events assumed in the model.

[Figure 2 Goes Here]

3.1. Generation of WOM

The process that generates WOM activity for product *j* during period *t* is given by the following dynamic panel data model:

$$\begin{aligned} N\_WOM_{jt} &= \alpha_0 + \alpha_W \cdot N\_WOM_{j,t-1} + \alpha_A \cdot N\_AD_{jt} + \alpha_P \cdot N\_PBL_{jt} + \alpha_x{}' x_{jt} \\ &\quad + \alpha_S S_{j,t-1} + \alpha_Q Q_{j,t-1} + \alpha_\sigma \sigma^2_{j,t-1} + \varepsilon_{1,jt}, \qquad \forall t = 1, 2, \ldots, T_j. \end{aligned} \tag{1}$$

where N_WOM_{jt}, N_AD_{jt}, and N_PBL_{jt} are the numbers of WOM messages, media advertising messages, and media publicity messages, respectively, for product *j* during period *t*. x_{jt} is a vector containing both time-varying and time-invariant observable product attributes (such as product characteristics, time trend, and seasonality dummies). $S_{j,t-1}$ denotes the sales of product *j* (i.e., number of new adopters) in the previous period. $Q_{j,t-1}$ represents consumers' mean perception of product *j*'s quality given the information available at the beginning of period *t-1*. A higher-quality product presumably could lead to a greater amount of consumer word of mouth. $\sigma^2_{j,t-1}$ represents consumers' uncertainty about product *j*'s quality. $Q_{j,t-1}$ and $\sigma^2_{j,t-1}$ are generated by the Bayesian learning model, described in Section 3.3. Previous research has shown that risk-averse consumers derive refrain from purchase when uncertainty is high (e.g., Roberts and Urban 1988; Erdem and Keane 1996); however, there has been no empirical evidence regarding how uncertainty influences the level of WOM. We hypothesize that higher uncertainty will decrease WOM because consumers do not want to jeopardize their credibility by spreading the word on a product whose quality they are uncertain about (Stephen and Lehmann 2009).

Note that the time subscripts represent the sample periods during which WOM occurs and do not necessarily start with the product release; particularly, consumer WOM can precede the actual product launch due to high consumer anticipation and/or pre-release marketing efforts, a phenomenon prevalent in many product categories ranging from movies, video games and popular books, to personal electronics such as the *Wii* console and Apple Inc.'s *iPhone*. Thus this pre-release buzz should be an integral part of a dynamic system of new product adoption and consumer WOM. Also, T_j can vary across products, allowing for an unbalanced panel, a desirable feature for researchers wishing to incorporate an ever growing dataset due to subsequent product introductions. The error term $\varepsilon_{1,jt}$ is assumed to consist of a mean-zero unobserved product-specific factor that is fixed over time ($\eta_{1,j}$) and an unobserved idiosyncratic time-varying error term ($\nu_{1,jt}$). We allow $\eta_{1,j}$ to correlate with the observed variables in Eq. (1) while assuming that the time-variant idiosyncratic error, $\nu_{1,jt}$, is uncorrelated with the regressors and is not serially correlated. With all the right-hand variables in Eq. (1) collected in a vector, $w_{1,jt}$, the formal assumptions on the error terms are:

$$\begin{aligned}
&\varepsilon_{1,jt} = \eta_{1,j} + \nu_{1,jt}, \\
&E[\eta_{1,j}] = 0,\ E[\nu_{1,jt}] = 0, E[\eta_{1,j}\nu_{1,jt}] = 0,\ \forall t = 1,2,...,T_j. \\
&E[\nu_{1,jt}\nu_{1,js}] = 0,\ t = 1,2,...,T_j \text{ with } s \neq t. \\
&E[\nu_{1,jt}w_{1,js}] = 0,\ \forall s = 1,2,...T_j;\ \forall t = 1,2,...,T_j. \\
&E[\eta_{1,j}w_{1,jt}] = E[\eta_{1,j}w_{1,js}],\ \forall s = 1,2,...T_j;\ \forall t = 1,2,...,T_j.
\end{aligned} \tag{2}$$

While $\nu_{1,jt}$ itself is serially uncorrelated, the total error term, $\varepsilon_{1,jt}$, can be serially correlated due to the presence of $\eta_{1,j}$. If we had assumed that $\eta_{1,j}$ was uncorrelated with all $w_{1,jt}$'s, the model would reduce to the standard "random effects" model (Greene 2003). However, this assumption is likely to fail because the unobserved product-specific factor (e.g., a video game release is tied to a blockbuster movie or a new toy) tends to correlate with the lagged dependent variable, $N\_WOM_{j,t-1}$, as well as other regressors that affect the level of WOM. The proposed model falls under the class of *correlated random effects models* previously proposed in the econometrics literature (Hausman and Taylor 1981; Ahn and Schmidt 1995). The main benefit of this specification is that it acknowledges the potential endogeneity of right-hand-side regressors while, unlike a fixed effects model, allowing us to identify the coefficients of time-invariant variables as well. We shall further discuss the implications of such a model form in Section 4.2.

3.2. The Adoption Process

The sales trajectory of product *j*, released during period T_j^R, is characterized by:

$$S_{jt} = \begin{cases} (M_{jt} - NS_{j,t-1})(\dfrac{\exp(V_{jt})}{1+\exp(V_{jt})}), & \text{for } t \geq T_j^R; \\ 0, & \text{for } t < T_j^R. \end{cases}$$

$$\text{where} \quad V_{jt} \equiv \beta_0 + \beta_A \cdot N\_AD_{jt} + \beta_P \cdot N\_PBL_{jt} + \beta_W \cdot N\_WOM_{jt} \qquad (3)$$

$$+ \beta_x{}' x_{jt} + \beta_S (NS_{j,t-1} / M_{jt}) + \beta_Q Q_{jt} + \beta_\sigma \sigma_{jt}^2 + \varepsilon_{2,jt}.$$

$$\varepsilon_{2,jt} = \eta_{2,j} + \nu_{2,jt}. \qquad (4)$$

S_{jt} is unit sales for product j during period t (which equals zero before its release period, T_j^R). M_{jt} is the market potential for product j. We allow the market potential to vary over time because, in our empirical context of the video game market, the installation base for the three major consoles (PlayStation 3, Wii, and Xbox 360) grew considerably over the sample period. Ignoring time-varying market potential might bias our model estimates. $NS_{j,t-1}$ is the cumulative sales of product j up to the end of period t-1. Product adoption rate is a logit function of marketing communications (N_AD_{jt} and N_PBL_{jt}), word of mouth (N_WOM_{jt}), product characteristics (x_{jt}), the cumulative pool of past adopters ($NS_{j,t-1}$), as well as consumers' mean perception (Q_{jt}) and uncertainty (σ_{jt}^2) about product j's quality. Although the demand equation is not explicitly derived from the consumer-level utility functions, the inclusion of mean quality perception and uncertainty in the demand equation is structurally consistent with consumer choice models based upon expected utility maximization when consumers face uncertain product attributes (e.g., Roberts and Urban 1988; Erdem and Keane 1996). The error term is also composed of a product-specific fixed factor ($\eta_{2,j}$), and a time-variant idiosyncratic error ($\nu_{2,jt}$) and we impose similar structure on the error terms as in Eq. (2): in particular, we allow $\eta_{2,j}$ to correlate with the regressors in Eq. (3) while assuming that the regressors are strictly exogenous with respect to $\nu_{2,jt}$ and that $\nu_{2,jt}$ itself is serially uncorrelated. We do not impose any cross-equation structure on the error terms, i.e., $\varepsilon_{1,jt}$ and $\varepsilon_{2,jt}$ can be freely correlated (or uncorrelated).

Note that this demand specification, similar to the general family of diffusion models, conceptualizes new product adoption rate as a function both of external influences through marketing efforts and of internal influences through social contagion (Mahajan and Peterson 1978; Sultan, Farley, and Lehmann 1990). However, the model has three distinct advantages over conventional new product sales models. First, unlike the typical diffusion model that predicates social contagion ("imitation") solely on the indirect measure of past adopters ($NS_{j,t-1}$), the current model also incorporates a direct measure of the scale of consumer WOM activities as a complementary construct of the strength of social contagion. Second, the proposed model allows pre-release WOM to affect post-release sales. Third, it enables us to investigate the exact process through which social contagion takes effect: namely, an informative mechanism (by influencing Q_{jt} and σ^2_{jt}), and a non-informative (persuasive) mechanism (as captured by β_W). Capturing the formation of consumers' quality perception is an important feature because the true quality of a new product is only imperfectly known to the consumers early in its lifecycle, and we model how consumers learn from others about the quality of the product. Here we use "quality" to broadly represent the vertically differentiating component (i.e., "the higher the better") of a product that is not immediately observable. For instance, for a video game, "quality" captures the extent to which a video game is enjoyable, fun, exciting to play, etc. We now describe the process by which consumers learn about the true quality of a new product.

3.3. Quality Learning

We model quality learning as a Bayesian updating process as in previous studies such as Erdem and Keane (1996) and Narayanan, Manchanda and Chintagunta (2005). Suppose the inherent quality of product j for consumer i is given by

$$Q_{ij} = Q_j + \varsigma_{ij},\ \ \varsigma_{ij} \sim N(0, \sigma^2_{\varsigma}). \tag{5}$$

where Q_j is the average true quality of product j across consumers, and σ^2_{ς} captures the heterogeneity in consumers' tastes. Before consumers obtain any information signal on quality, the prior distribution on Q_j is

$$\tilde{Q}_{j0} \sim N(Q_0, \sigma^2_0) \tag{6}$$

Note that although we assume that the prior belief is the same across products, different products can still differ in initial attractiveness due to observed product attributes and marketing activities as specified in Eq. (3). Consumers who have not adopted product j at the beginning of period t update their beliefs on Q_j from three information sources: media advertising, publicity, and WOM. All three sources are postulated to give consumers noisy signals about the true quality of the new product. Specifically, the quality signal from the i-th WOM message (or, equivalently, the i-th consumer who sends out a WOM message) about product j at time t is assumed to be distributed around the individual-specific quality, Q_{ij}, with an independent, normally distributed error:

$$WOM_{ijt} = Q_{ij} + \tilde{\upsilon}_{ijt}^{WOM}, \ \tilde{\upsilon}_{ijt}^{WOM} \sim N(0, \tilde{\sigma}_{WOM}^2). \tag{7}$$

Plugging Eq. (5) into Eq. (7), we have

$$WOM_{ijt} = Q_j + \upsilon_{ijt}^{WOM}, \text{ where } \upsilon_{ijt}^{WOM} \equiv \varsigma_{ij} + \tilde{\upsilon}_{ijt}^{WOM}. \tag{8}$$

It follows that $\upsilon_{ijt}^{WOM} \sim N(0, \sigma_{WOM}^2)$, where $\sigma_{WOM}^2 \equiv \sigma_{\varsigma}^2 + \tilde{\sigma}_{WOM}^2$.

The i-th advertising message and i-th publicity message for product j at time t, respectively, are given by:

$$AD_{ijt} = Q_j + \upsilon_{ijt}^{AD}, \upsilon_{ijt}^{AD} \sim N(0, \sigma_{AD}^2) \tag{9}$$

$$PBL_{ijt} = Q_j + \upsilon_{ijt}^{PBL}, \upsilon_{ijt}^{PBL} \sim N(0, \sigma_{PBL}^2) \tag{10}$$

Given the distributional assumptions on the prior quality belief and the informational signals, the posterior belief on Q_j at time t can be obtained via the Bayes' theorem: specifically, the posterior belief on Q_j also follows a normal distribution with mean Q_{jt} and variance σ_{jt}^2:

$$\tilde{Q}_{jt} \sim N(Q_{jt}, \sigma_{jt}^2) \tag{11}$$

Q_{jt} is the mean quality perception and σ_{jt}^2 is the variance that captures consumers' uncertainty about true quality. Assuming that the signal noises are independent of each other, we obtain

$$\frac{1}{\sigma_{jt}^2} = \frac{1}{\sigma_{j,t-1}^2} + \frac{N\_WOM_{jt}}{\sigma_{WOM}^2} + \frac{N\_AD_{jt}}{\sigma_{AD}^2} + \frac{N\_PBL_{jt}}{\sigma_{PBL}^2} \tag{12}$$

The inverses of σ_{WOM}^2, σ_{AD}^2 and σ_{PBL}^2 represent the signal precision of each information source. As more information about product j is acquired, Eq. (12) shows that the precision increases, i.e., the uncertainty parameter σ_{jt}^2 decreases. The mean of the posterior belief is updated as follows:

$$\begin{aligned} Q_{jt} &= \sigma_{jt}^2 \cdot \left(\frac{Q_{j,t-1}}{\sigma_{j,t-1}^2} + \frac{\sum_{i=1}^{N\_WOM_{jt}} WOM_{ijt}}{\sigma_{WOM}^2} + \frac{\sum_{i=1}^{N\_AD_{jt}} AD_{ijt}}{\sigma_{AD}^2} + \frac{\sum_{i=1}^{N\_PBL_{jt}} PBL_{ijt}}{\sigma_{PBL}^2}\right) \\ &= \sigma_{jt}^2 \cdot \left(\frac{Q_{j,t-1}}{\sigma_{j,t-1}^2} + \frac{N\_WOM_{jt} \cdot \overline{WOM}_{jt}}{\sigma_{WOM}^2} + \frac{N\_AD_{jt} \cdot \overline{AD}_{jt}}{\sigma_{AD}^2} + \frac{N\_PBL_{jt} \cdot \overline{PBL}_{jt}}{\sigma_{PBL}^2}\right). \end{aligned} \tag{13}$$

where $\overline{WOM}_{jt}$, $\overline{AD}_{jt}$ and $\overline{PBL}_{jt}$ are the mean signals from WOM, advertising and publicity, respectively, on Q_j during period t. The mean quality perception Q_{jt} and variance parameter σ^2_{jt} generated from this learning mechanism then influence WOM generation and new product adoption pattern as characterized in Eq. (1) to Eq. (4).

4. Data and Estimation

4.1. Data

We apply the model to the U.S. video game market. Video game software constitutes an $11.6 billion market in 2008, larger than both the music ($10.4 billion) and theatrical movie markets ($9.6 billion), and is the largest entertainment sector second only to the DVDs ($21.6 billion). It is estimated that 44% of adults aged 18 and above play some form of video game (Mintel 2008). The video gaming market consists of console/handheld games ($8.6 billion), online games ($1.4 billion), and mobile phone games ($641 million). We focus our empirical study on the largest segment of this market: video game titles developed for the three seventh-generation home consoles – Sony's PlayStation 3, Microsoft's Xbox 360, and Nintendo's Wii.

Our sample includes the 160 top-selling console games released between January 2007 and March 2008. For each title, we collected data on its release date, genre (e.g., Action, Fighting, Sports, Music/Dance), ESRB rating (Everyone, Everyone 10+, Teen, and Mature), console platform (i.e., PlayStation 3, Xbox 360, and Wii), as well as monthly sales and average monthly retail prices during the 15-month sample period. Since the adoption of video game software requires the ownership of the compatible hardware, we also collected data on the monthly sales of the three consoles from their respective launch dates to control for the evolving hardware installed bases**.** Figure 3 illustrates the distinct growth patterns for the three game hardware platforms during the sample period. Our sample consists of 33% Wii games, 44% Xbox 360 games, and 23% PlayStation 3 games.

[Figure 3 Goes Here]

The advertising data were collected from four major monthly video game magazines – *Game Pro*, *Electronic Gaming Monthly*, *Nintendo Power*, and *Xbox Magazine*.[3] All advertisements on

[3] Although it would be desirable to obtain advertising data on other media such as TV and online, such data were unavailable to us. However, according to the video gaming industry executives who we interviewed, advertising across media is often highly correlated.

the sample video games were counted in each issue of the four magazines, together with the size of each advertisement (including half-page, full-page, 2-page, and 4-page ads). The page count was weighted by the circulation of a given magazine to obtain a measure of total advertising impressions in each month, which is used as the measure for N_AD_{jt}. The publicity data were compiled from 36 major print and online media sources that regularly report and review newly released video games, including *Yahoo! Video Games*, *IGN.com*, *Maxim Online*, *USA Today*, and *GameSpot*. (A full list of these media sources is available in the Web Appendix.) Only articles that offer detailed descriptions or opinions on a video game were recorded: in other words, if an article only mentions a game title in passing, without providing any detail or assessment, it was excluded from our publicity measure. For each publicity piece, we collected the publishing date and, if present, the reviewer score accompanying the article. Since different publications employ different scoring schemes, we converted all the scores to a 10-point scale; for instance, if a game receives three out of four stars from a reviewer, the score is coded as 7.5. The average reviewer score in that month provides a direct measure of $\overline{PBL_{jt}}$. Since the media reports come from a mix of print and online, general-interest and gaming-specialty sources, it is not possible to find a unifying weighting scheme such as magazine circulation to adjust for their disparate influences. A close observation of the data reveals that the more influential sources tend to have a more comprehensive coverage of new video games while less influential sources tend to cover only the more popular titles. Therefore, we used the logarithm of the number of news articles for a given title in each month as a measure for N_PBL_{jt}.

To measure consumer WOM, we utilized a unique data set compiled from a database maintained by *Nielsen BuzzMetrics* that assembles the complete user-generated content of over 200 online discussion boards and forums dedicated to video gaming. For each video game in our sample, we used a computer program to collect all the posts that referenced a particular game title. Usually, multiple query terms were applied to ensure better coverage (e.g., “Mario Galaxy” and “Super Mario Wii” for *Super Mario Galaxy*). This total number of posts on a game in a given month provides a measure of N_WOM_{jt}. Compared to most extant research on online WOM that only uses data from one or two websites, our data set provides a much broader coverage of the entire universe of consumer online WOM in, and therefore should increase our confidence in the validity of the empirical findings.

Table 1 reports the key descriptive statistics of the data for the 160 games in our sample.

[Table 1 Goes Here]

4.2. The Estimation Approach

4.2.1. Endogeneity

In both the WOM and demand equations, we allow unobserved factors ($\eta_{1,j}$, and $\eta_{2,j}$), to be correlated with the explanatory variables in the two equations. For instance, if an econometrically unobserved product attribute (or a measurement error in the quality construct) persists over time in the sales equation, it can be correlated with price, advertising, publicity, WOM, as well as cumulative past sales. Such endogeneity, if unaccounted for, would result in inconsistent coefficient estimates for these variables. A conventional technique to circumvent this problem with panel data is a fixed-effect estimator that transforms the data into deviations from the group means and hence utilizes only "within-group" variation. However, this estimator has two important drawbacks: first, coefficients of time-invariant variables (e.g., game genres, console platforms) cannot be identified, so we would not be able to measure their impact on WOM or sales; second, the fixed-effect estimator can be inefficient because it ignores the between-product variation in the data. Another alternative is to find external instruments for the potentially endogenous regressors: these variables, excluded from the demand equation, should correlate with, say, WOM and cumulative past sales, but should be uncorrelated with $\eta_{2,j}$. Finding and verifying such instruments empirically is rarely feasible.

Hausman and Taylor (1981) proposed an instrumental variable estimator that takes advantage of the panel structure of the data to resolve the endogeneity issue. Boulding and Christen (2003) applied this approach to evaluating the market entry order effect on firm performance. The intuition of this identification strategy is as follows: under certain assumptions on the first and second moments similar to those in Eq. (2), one can use the mean-differenced time-varying variables as valid instruments to help identify the parameters for these variables. This is because $(w_{jt} - \overline{w}_j)$, where w_{jt} is a potentially endogenous time-varying variable (such as *N_WOM*, *N_AD and N_PBL*) and $\overline{w}_j$ is its within-product mean, is orthogonal to the product-fixed effects, $\eta_{1,j}$ and $\eta_{2,j}$. Moreover, if we know that certain time-varying regressors are exogenous, they offer extra instruments through their within-product means, a major advantage that enables hypothesis testing based on over-identifying restrictions and also helps identify any endogenous time-invariant variable. In the WOM equation, $N\_WOM_{j,t-1}$, N_AD_{jt}, N_PBL_{jt}, and $S_{j,t-1}$ are potentially endogenous and are thus instrumented with their mean-differenced values, while $Q_{j,t-1}$, σ_{jt}^2 and the time-varying elements in x_{jt} offer extra instruments through their within-product means. In the sales equation, we treat N_WOM_{jt}, N_AD_{jt}, N_PBL_{jt}, and $NS_{j,t-1}/M_{jt}$, and price as endogenous, the rest of the time-varying variables in x_{jt}, together with Q_{jt} and σ_{jt}^2, offer extra instruments.

4.2.2. The GMM estimator

We construct a generalized method of moments (GMM) estimator. Let z be a vector of instruments that are exogenous to the error terms in Eq. (1) and Eq. (3). The GMM estimator is given by the solution to the following optimization problem:

$$\hat{\theta}_{GMM} = \arg\min_{\theta\in\Theta} \varepsilon(\theta)' ZWZ' \varepsilon(\theta), \tag{14}$$

where $\varepsilon \equiv [\varepsilon_1;\varepsilon_2]$, and ε_1 and ε_2 are the stacked error terms from Eq. (1) and Eq. (3). Z is a block diagonal matrix with the instruments corresponding to ε_1 and ε_2 occupying the diagonal blocks. W is a symmetric positive definite weighting matrix, and the efficient GMM estimator is obtained when the "optimal" weighting matrix, $E[(Z'\varepsilon\varepsilon' \mathrm{Z})]^{-1}$, is applied based on a consistent estimator of θ. The advantage of using the inverse of the variance-covariance matrix of the moments as the weighting matrix is that higher weights are given to the moments with lower variance.

Write $\alpha \equiv [\alpha_0, \alpha_{\mathrm{x}}', \alpha_A, \alpha_P, \alpha_W, \alpha_S, \alpha_Q, \alpha_\sigma]'$, $\beta \equiv [\beta_0, \beta_{\mathrm{x}}', \beta_A, \beta_P, \beta_W, \beta_S, \beta_Q, \beta_\sigma]'$, and $\mu \equiv [\sigma_0^2, \sigma_{WOM}^2, \sigma_{AD}^2, \sigma_{PBL}^2]'$. Note that while the WOM equation is linear in the error term, the demand equation is not. However, it can be re-written as

$$\ln\left(\frac{S_{jt}}{M_{jt} - NS_{j,t-1}}\right) - \ln\left(1 - \frac{S_{jt}}{M_{jt} - NS_{j,t-1}}\right) = V_{jt}, \text{ for } t \geq T_j^R. \tag{15}$$

This inversion enables the use of standard instrumental variables and also allows all the parameters contained in β to enter the GMM objective function linearly so that the first-order condition can be analytically solved within the optimization routine (Berry 1994; Berry, Levinsohn, and Pakes 1995). As a result, both α and β enter the GMM objective function linearly, and only μ enters the objective function nonlinearly.

The estimation approach proceeds as follows: for each set of μ, the latent variables Q_{jt} and σ_{jt}^2 are computed and plugged into the GMM optimization problem so that the linear parameters are analytically found that minimize the GMM objective function conditional on the nonlinear parameters, $[\hat{\alpha}(\mu);\hat{\beta}(\mu)]$. The algorithm then searches over the space of μ until the GMM objective function reaches its global optimum.

Theoretically, the true quality of each game, Q_j, can be identified through a joint estimation of the WOM equation, demand equation, and the quality learning equation. For instance, the across-game differences in their long-term sales patterns allow the identification of these parameters. However, this would require another 160 nonlinear parameters to estimate. An alternative is to estimate Q_j's in a first-step estimation from the quality learning process. Specifically, the time-specific mean publicity signal, $\overline{PBL}_{jt}$ alone should be an asymptotically consistent estimate of Q_j. In order to improve the efficiency of this estimator, we supplemented the main data set on publicity with another 12 months of data on reviewer ratings on IGN.com (April 2008 to March 2009). To ensure that these two data sets can be pooled, we ran a *t*-test on the ratings before and after April 2008 and did not detect a statistically significant difference between the means.

Another estimation issue is that, though the variance parameter σ_{jt}^2 evolves deterministically, the mean quality perception Q_{jt} evolves stochastically from the econometrician's viewpoint: the consumers observe the signals from all three sources, but the econometrician only observes $\overline{PBL}_{jt}$ quantitatively through observed reviewer scores. This means that $\overline{WOM}_{jt}$ and $\overline{AD}_{jt}$ need be treated as random variables in the estimation approach[4]:

$$\overline{WOM}_{jt} \sim N(Q_j, \frac{\sigma_{WOM}^2}{N\_WOM_{jt}}); \ \overline{AD}_{jt} \sim N(Q_j, \frac{\sigma_{AD}^2}{N\_AD_{jt}}) \tag{16}$$

We simulate 800 random draws each for $\overline{WOM}_{jt}$ and $\overline{AD}_{jt}$ per period, construct the serially correlated vectors of mean quality perception, $\{Q_{jt}\}_{t=1}^T$, and use the Monte Carlo means for $\{\hat{Q}_{jt}(\mu)\}_{t=1}^T$. Note that while we do not explicitly model the valence of WOM, it is implicitly

[4] Potential text mining techniques might be able to link the contextual and linguistic characteristics of the WOM messages to a quantitative measure for the quality signal contained in these messages. However, no such techniques have been established. Therefore, we chose to remain agnostic about the detailed content of the WOM messages aside from the relatively innocuous assumption that, on average, they reflect the true quality of the focal product.

accounted for in the learning process under the reasonable assumption that consumers spread truthful messages about their experience with the new product. In other words, for a high-quality product, consumers' perception of its true quality, Q_{jt}, will gradually adapt from the prior mean to its true value, approximating the effect of predominantly positive WOM.

4.3. Identification

The linear parameters in the demand equation are identified through the within- and between-product variations in the marketing mix variables and WOM measures. The signal variances of information sources are essentially identified through the different sales trends of higher- and lower-quality games over time. Since the signal variances are not identifiable separately from the prior variance, we normalize σ_0^2 to one.

5. Results

5.1. Parameter Estimates

We report three sets of parameters estimated from the full model in Table 2: parameters pertaining to the development of WOM (Eq. (1)), parameters in the new product diffusion model (Eq.(3)), and parameters characterizing the quality learning process (Eqs. (5) – (13)).

[Table 2 Goes Here]

The left panel in Table 2 presents the coefficients of the demand equation. All three modes of communication – WOM, advertising, and media publicity – directly exert significantly positive effects on the adoption rate of new video games. This captures the *persuasive* effect of communication irrespective of the quality signals contained in these messages.

Noticeably, the coefficient of WOM volume (N_WOM_{jt}) is significantly positive even when the cumulative number of past adopters ($NS_{j,t-1}$) has been controlled for. This underscores the need to directly measure WOM and integrate it in a new product diffusion model. On the other hand, the positive coefficient of $NS_{j,t-1}$ suggests that there is a residual social contagion effect beyond what is captured by the online WOM measure alone, such as offline WOM communication or observational learning. Taken together, this implies that both the direct measure (such as online WOM volume) and indirect measure (such as accumulative past adopters) of social contagion should be incorporated in a durable goods diffusion model.

The price coefficient is negative and statistically significant. The trend coefficient is also negative. Our sales equation already accounts for the shrinking pool of potential adopters due to the exit of past adopters, so the negative trend reflects the decaying appeal of a video game as it ages, a feature shared by many novelty-driven product categories such as movies, DVDs, popular fictions, and fashion goods (e.g., Eliashberg, Elberse, and Leenders 2006).

As expected, the mean quality perception (Q_{jt}) has a positive effect on adoption. The level of uncertainty about the quality of a new video game (σ_{jt}^{2}) reduces diffusion rate, meaning that consumers are risk-averse: even for an average-quality video game, informative signals reduce consumers' uncertainty about the product quality and therefore increase adoption rate.

The results confirm the highly seasonal nature of video game demand. Demand slumps in the first quarter, picks up in the second quarter, drops in the third quarter, hits its nadir in October and moderately rises in November. It then peaks in the major gift-buying season of December. Mature-rated games sell significantly less than Everyone-, Everyone-over-10 (E10)- or Teen-rated games. This mirrors the movie market where R-rated movies generally have lower demand than movies with other MPAA ratings. The three console platforms also have marked differences in the software adoption rate: PlayStation 3 (used as the base category here) has the highest software purchase rate per installed hardware base on average, followed by Wii, whereas Xbox 360 has the lowest. This is probably due to the fact that the Xbox 360 console was released a year before (November 2005) the other two consoles were launched (November 2006). Since a new owner of hardware often stocks up on software titles, a newer console platform tends to enjoy a higher software-to-hardware ratio than an older platform. Among various game genres, the most popular ones include Music/Dance games (e.g., *Guitar Hero*), Family/Children games (e.g., *Wii Play*), and Role-Playing games (e.g., *Mass Effect*), possibly reflecting the broader demographic appeal of such genres.

Table 2 reports the coefficient estimates in the WOM evolution equation. As expected, lagged WOM volume has a significantly positive effect on current WOM, consistent with the momentum (or cascade) of WOM communication. The effect of advertising on WOM is statistically insignificant, whereas media publicity has a significantly positive effect. Lagged sales also positively affect WOM volume, as expected given that recent adopters are most likely to talk about their purchases and experiences. The mean quality perception (Q_{jt}) positively affects WOM volume, meaning that consumers are more likely to spread WOM about higher-quality products, even after controlling for lagged sales.[5] Uncertainty ($\sigma_{jt}{}^2$) has a negative coefficient: higher uncertainty regarding product quality decreases the volume of WOM. This finding is consistent with the social-capital based theory of WOM transmission (e.g., Stephen and Lehmann 2009): in the presence of limited information and high uncertainty, potential transmitters refrain from spreading WOM for fear of damaging their reputation or credibility.,.

The lower right panel in Table 2 presents the variance parameters characterizing the quality learning process. The WOM and publicity signal variances, ln(σ^2_{WOM}) and ln(σ^2_{PBL}), are estimated to be relatively small, implying that WOM and publicity provide useful information regarding the true quality of a new video game. The estimate for the advertising signal variance, ln(σ^2_{AD}), is very large and imprecisely estimated (i.e., with a large standard error), suggesting that advertising is an extremely noisy signal for an average game. In other words, advertising has a significantly positive persuasive effect but no informative effect.

5.2. Model Comparisons

The proposed model (M1) provides good fit to the data. The correlation between actual and predicted sales across observations is 0.87, and that between actual and predicted WOM volume is 0.95. We construct three benchmark models to assess two main features of the proposed model: (i) the value of incorporating direct measures of WOM in a new product sales model; and (ii) the value of explicitly modeling quality learning in a diffusion framework. The first benchmark model (B1) excludes the direct WOM measure and variables related to quality learning. The second benchmark (B2) utilizes the WOM measure but excludes the learning variables, and the third benchmark (B3) utilizes the WOM and quality measures yet assumes instant learning (i.e., the true quality of a new product is revealed as soon as any information signal occurs), a specification primarily intended to test the validity of the assumed Bayesian updating process. In addition, we also estimated a version of the proposed model (M2) with only the demand equation for two reasons: First, the results reported in Table 2 arise from a joint estimation of the sales equation and the WOM equation. If the WOM development equation were misspecified, this

[5] To detect potential U-shaped relationship between perceived quality and WOM volume, we estimated a specification with a quadratic specification of Q_{jt} in the WOM generation equation. The quadratic term was statistically insignificant (parameter estimate = 1.2, *t*-value = 1.29).

might result in inconsistent estimates of the demand equation; therefore, it would be desirable to estimate the demand side separately to check the robustness of the results discussed above. Second, since the benchmark models only concern the sales equation, it would be necessary to estimate the demand side of the proposed model to have a uniform scale of performance comparison.

We first compare the parameter estimates in M1 (joint estimation of the demand and WOM equations) and M2 (estimation of the demand equation only). Most estimates are remarkably similar in these two models. The only notable difference is that the coefficient of Q_{jt} becomes insignificant at the 0.10 level in M2 although its value remains essentially the same as in M1. This suggests that joint estimation of the demand equation and the WOM equation is valid and improves efficiency. The estimates of the three benchmark models are reported in Table 3. Since a GMM estimator of each benchmark model not only differs in the number of parameters but also by construction necessitates a different set of moment conditions, statistics (such as the Wald and Lagrange multiplier statistics) used to test null hypotheses for nested models cannot be applied. We use the model and moment selection criteria (MMSC) for non-nested GMM models proposed by Andrews and Lu (2001) to compare the alternative models. The MMSC are based on the *J*-test statistic for testing over-identifying restrictions with extra terms rewarding the use of fewer parameters and the use of more moment conditions. The MMSC-AIC and MMSC-BIC are analogous to the widely used likelihood-based AIC and BIC selection criteria, and a smaller value of either statistic denotes a better fit. The result shows that the proposed model with direct WOM and learning (M2) outperforms the three benchmarks on both the MMSC-AIC and MMSC-BIC criteria. When the model with no learning (B2) and the model with instant learning (B3) are compared, B2 actually has a slightly better fit than B3, substantiating the Bayesian updating construct; that is, the quality belief is gradually updated through a stream of informational signals rather than instantly and conclusively formed.

[Table 3 Goes Here]

It is worthwhile to notice that B2 and B3 appear to overestimate the direct effect of WOM (0.046 and 0.025 vs. 0.013 in the proposed model) due to the omission of the quality learning mechanism. Since WOM is inherently endogenous, i.e., a higher quality product tends to elicit more WOM, failure to control for consumers' quality perception would result in an overestimation of the marginal contribution of WOM to sales. Our empirical result suggests that

WOM still has a significantly positive effect on sales, even controlling for perceived quality and uncertainty; however, the magnitude of this direct effect is much smaller, compared to when perceived quality is not accounted for. The price coefficient is also larger in magnitude in the proposed model than in the benchmarks. These results suggests that the including the learning mechanism can help researchers obtain more accurate marginal effects of WOM and marketing mix variables.

5.3. The Learning Process

To illustrate the quality learning process, in Figure 4 we graph the updating of Q_{jt} for five video game titles from the month prior to their respective releases till the ninth month after release. Since we have normalized the prior mean quality perception to zero for identification, the updating curve always starts at zero. For certain games (e.g., *Super Paper Mario*), there is already a significant amount of quality learning before product launch due to pre-release advertising, publicity and/or WOM activity in anticipation of the game's actual launch. Our model is able to capture this phenomenon because the demand model allows for pre-release quality signals to affect post-release sales patterns. Figure 4 demonstrates that game titles vary substantially in the pattern and speed of quality updating. Certain games, such as *Major League Baseball 2K7 (PS3)* and *Lost Planet: Extreme Condition (Xbox)*, come very close to revealing their true qualities by Month 3 to 4; however, for games such as *Sonic the Hedgehog (PS3)*, the quality learning curve is still quite steep by Month 9. Such variation in learning patterns is driven by the differences in the volume as well as the precision of informational sources. Another interesting finding is that the quality learning process is not necessarily monotonic, due to the noise inherent in all three information sources, as reflected in the updating pattern of *Major League Baseball 2007 (PS3)*[6]. Non-monotonic patterns capture an important aspect of quality learning: although in the long run, the market will converge on the true quality of the product after sufficient information has been revealed, in the short run, noisy signals (e.g., an ill-executed advertising campaign, biased publicity) are capable of temporarily shifting the quality perception away from the true quality.

[Figure 4 Goes Here]

[6] Technically, our model is able to discern these fluctuations because of the information contained in the time-varying reviewer scores that are used as a proxy for $\overline{PBL}_{jt}$.

Another dimension of quality learning is the process by which uncertainty about new product quality is reduced through informative marketing communication and WOM. Figure 5 depicts the cumulative percentage decrease in uncertainty variance (σ_{jt}^2) for the same five titles as reported in Figure 4. The pattern of variance reduction varies considerably across titles, ranging from as much as 80% for *Super Paper Mario* to as little as 10% for *Sonic the Hedgehog* by Month 9. Both Figure 4 and Figure 5 reveal that, for a new video game, quality learning is the fastest in the first two to four months and slows down in later months. Another important finding is that a substantial amount of uncertainty persists even after Month 9: quantitatively, averaging across all the titles in our sample, the variance parameter is reduced to approximately 82.4% in one month, to 70.4% in three months, and to 65% in nine months. Previous research on learning about services or frequently purchased goods has found evidence for much faster quality learning. For instance, Iyengar, Ansari, and Gupta (2007) reported that a consumer's uncertainty about the quality of a wireless plan is reduced to 10% by the fifth months. Our results show that quality learning about a durable product occurs much more gradually because consumers must only rely on marketing communications and others' experiences rather than on their own consumption experience as in services or frequently purchased goods categories.

[Figure 5 Goes Here]

5.4. The Role of Product Innovativeness in Communication Effectiveness

Past literature has suggested that the degree of product innovativeness may substantially influence the returns of marketing actions (Assmus, Farley, and Lehmann 1984; Lodish et al. 1995; Lee and O'Connor 2003; Srinivasan et al. 2009). For instance, Srinivasan et al. showed that advertising effectiveness of pioneering innovations in the automobile industry is much higher than that of minor innovations in terms of firms' market capitalization. Given our primary interest in quantifying the effects of three types of product-related communication (i.e., advertising, media publicity, and consumer WOM) on new product performance, it would be of both theoretical and substantive interest to explore how their effectiveness depends on the level of innovativeness (major vs. minor) of a new video game.

To this aim, we created a sub-sample of video games that represent a *major innovation* as opposed to merely a *minor update*: a video game is considered a major innovation if there has been no prior version or edition of the game released on the current console platform; it usually involves a new set of characters, a fresh plot, or/and a novel form of interactivity. For instance, Xbox 360 *Mass Effect* is considered a major innovation, while PlayStation 3 *Madden NFL 08* is not because the latter has a prior version, *Madden NFL 07*, released on the same console. This sub-sample consists of 118 games in total.

The parameter estimates for the major innovations are presented in Table 4. While most coefficients are highly consistent with the full sample results in Table 2, one major difference stands out: the parameter for the advertising signal variance becomes much smaller and is tightly estimated, indicating that, while advertising is generally not informative for an average video game, it is informative for games of high innovativeness. Our result reaffirms the previous finding (e.g., Lodish et al. 1995) that advertising tends to work better when the message contains a high level of "newness" to the consumers.

[Table 4 Goes Here]

To illustrate the differential importance of communication modes in consumers' quality learning process between an average game and a highly innovative game, we demonstrate the relative importance of the three information sources by decomposing the variance reduction into the percentage attributable to advertising, to publicity, and to WOM in Figure 6. As shown in Figure 6(A), for the average video game, the informative effect of advertising is virtually zero due to the noisy nature of advertising signals in general. WOM remains the most prominent information source about product quality throughout the product lifecycle: In the first three months following the product release, WOM contributes to about 70% of the quality learning while publicity makes up the remaining 30%; the informative role of WOM then further rises in the ensuing three months, and by Month 8, WOM has become the sole source of quality information. On the other hand, as illustrated in Figure 6(B), for major innovations, advertising contributes up to 15% of the learning in the initial months, and WOM accounts for a significantly lower proportion of the learning in the initial three months (under 55%) than for the average game (70%). This implies that firms' own marketing communication efforts are more important for products of higher innovativeness because of a relatively weaker support from consumer WOM alone. However, for both average and highly innovative products, WOM is the most important means through which consumers learn about product quality.

[Figure 6 Goes Here]

6. Managerial Implications

6.1. Short-Term Elasticities: WOM and Marketing Communications

Table 5 reports the mean same-month elasticities of WOM, advertising, and publicity for video game titles in our sample (e.g., 1% increase in first-month WOM volume leads to 0.113% increase in first-month unit sales on average). We also report the mean elasticities for the top quality quartile (i.e., 25% titles with the highest quality) and bottom quality quartile (i.e., 25% titles with the lowest quality) to demonstrate how the effectiveness of each communication mode depends on the quality of a video game.

[Table 5 Goes Here]

Several observations are in order. First, media publicity has the largest sales elasticity overall, followed by WOM, and advertising has the lowest elasticity. In terms of temporal patterns, for both media publicity and consumer WOM, elasticity is highest in the release month and declines subsequently, whereas advertising elasticity exhibits an inverted U-shaped pattern that peaks in Month 2.

Second, WOM elasticity is much greater for higher-quality games than lower-quality games: the top quality quartile has a first-month elasticity that is seven times as much as the bottom quality quartile. This pattern persists over time, and is a bit different than the effects for advertising and publicity, where the same-month elasticities can be larger or smaller for higher- vs. lower-quality games.

Third, advertising elasticity does not show discernible difference between higher- and lower-quality games, which is consistent with the finding that advertising mainly has a persuasive effect on video game sales.

Lastly, the short-term elasticity of media publicity shows a moderate difference between higher- and lower-quality games: it is greater for higher-quality games in the first two post-launch months yet, for lower-quality games, it is slightly higher in the ensuing two months. Since our primary research objective is to understand the three roles of marketing communications in the new product adoption process as portrayed in Figure 1, we decompose the total elasticity of media publicity into three components: the persuasive effect, the informative effect, and the buzz effect. Quantitatively, 1% increase in first-month publicity leads to 1.17% increase in same-month unit sales due to its persuasive effect (85% of total elasticity), 0.04% increase in sales due to its own informative effect (3%), and another 0.16% increase in sales due to its buzz effect (12%). This percentage composition is fairly consistent through time periods and across quality strata. The finding that a significant portion of the publicity effect on sales is achieved through its indirect impact on consumer WOM suggests that marketing communications – in particular, media publicity in our empirical context – can play a major role in seeding and facilitating WOM and hence increasing sales. In fact, the buzz effect is much larger than its own informative effect (12% vs. 3%) here. If the mechanism of buzz development were omitted, one might mistakenly ascribe this to the informational effect of publicity itself and arrive at suboptimal managerial recommendations. For instance, our finding suggests that the exact informational content of media coverage plays a very small role in consumers' quality learning process since publicity mainly promotes awareness/prestige and stimulates buzz, which means that, at least in the video game market, "any publicity is good publicity." Even for the games in the bottom quality quartile, the net effect of publicity is positive and substantial.

To further understand the relationship between WOM effectiveness and product quality, we decompose the total WOM elasticity into a component due to the informative effect and a component due to the persuasive effect in Figure 7. It is apparent from Figure **7** that the composition of WOM elasticity, in addition to its total size, depends on quality. The upper panel reveals that, for a game in the 20% top quality group, the informative effect of WOM dominates in the release month but becomes similar in size with the persuasive effect for the rest of a game's lifecycle. This implies that if a firm marketing a high-quality video game intends to utilize buzz to educate potential buyers about its quality, it is critical to facilitate WOM conversations in the first few weeks following release. Also, monitoring and potentially managing the contents of WOM activities is much more important immediately following product release, since, later in the game's lifecycle, WOM conversations may contribute more to awareness and the impression of popularity rather than to informing consumers about a game's quality. The lower panel indicates that, for lower-quality games, a small informative effect (roughly a third of that of a high-quality game) persists as the dominant mechanism while the persuasive effect remains miniscule during the game's lifecycle. These findings support the highly informational nature of consumer WOM communication, and suggest that firms' strategic efforts to stimulate buzz can only be effective when the inherent product quality is high.

[Figure 7 Goes Here]

To examine how product innovativeness may influence the effectiveness of each communication type, we also calculated the short-term sales elasticities for the major innovations only. The results are presented in Table A2 in the Web Appendix for the interested reader, but we report the main findings: For major innovations, the advertising elasticity is almost 100% higher than that for the average game, the WOM elasticity is 25-40% higher while publicity elasticity remains about the same. These findings broaden the current scope of the research on the relationship between product innovativeness and marketing mix productivity since most previous studies in this literature have been focused on advertising (Lodish et al. 1995; Srinivasan et al. 2009).

6.2. Long-term effects of buzz marketing

For marketers responsible for developing an integrated communication program for a new product, they not only wish to understand the size and composition of short-term effects of communication on sales, but also long-term effects. For instance, if a firm could design a program (e.g., sending samples to popular bloggers, designing viral videos) that increases release-month WOM volume by 10%, what would be the total long-term effect on sales and revenue? To answer this question, one has to consider the dynamic ramifications of this strategy: first, an increase in WOM activity not only leads to same-month sales growth, but also might lead to more WOM activity in subsequent months due to the momentum of social contagion; second, it would also speed up the consumers' quality learning process, which could also influence sales in the ensuing periods. Since our proposed model incorporates the dynamics in WOM evolution, quality learning, and new product diffusion in an integrated framework, it enables marketers to quantify the long-term ramifications of a proposed policy.

To illustrate this point, we implement a simulation where we increase the observed WOM volumes in the release month by 10% for all games in the sample, and simulate the monthly sales patterns given the parameter estimates. We let this policy change ripple through the dynamic system of WOM evolution, quality learning, and diffusion, while keeping other variables such as price, advertising and publicity unchanged. To compute the aggregate sales over time, we use a monthly discount rate of .995. The left panel in Figure 8 presents the median effects on sales and revenue by quality quartile. On average, a 10% increase in release-month WOM volume leads to a moderate increase of approximately 4,000 in unit sales, or $182,000 in revenue (a 1.5%

increase). However, the magnitude of this effect critically depends on the quality of the game: for the titles in the top quality quartile, this change translates to almost $1.1 million extra revenue per game (a 4% increase in long-term revenue); for the second quality quartile, it is only about one-third of the effect in the top quartile, and the effect for the lowest-quality quartile is as little as 0.22%. This further strengthens our aforementioned finding that buzz marketing as a new product promotion tool is only useful to the extent that the product has high intrinsic quality.

[Figure 8 Goes Here]

6.3. Long-term effects of marketing communication

Instead of directing influencing consumer WOM through buzz marketing programs, marketers can also choose to leverage advertising or publicity to facilitate WOM and increase sales. Given our empirical finding that media publicity for new video games exhibit all three effects – persuasive, informative, and buzz – it is interesting to explore the long-term effect of publicity. The right panel of Figure 8 presents the median long-term effects of a 5% increase in release-month publicity. The result shows that it increases sales by 12,000 units per game and revenue by $600,000 (or 4.4%). As in the policy simulation regarding WOM, the long-term effect of publicity is greater for higher-quality games. However, in percentage terms, the differential across various quality strata is less steep: increasing the publicity activities for games in the two lowest quality quartiles still leads to a robust 2.6-3.6% increase in revenue. Combined with cost-side information, marketers can use this approach to calculate the ROI for alternatives communication strategies and select the option that maximizes their marketing productivity.

7. Conclusions and Limitations

We propose a dynamic model of new product diffusion and WOM development that accounts for consumers' gradual learning about a new product's quality. It captures the informative and persuasive effects of marketing communications and WOM in an integrated framework and allows us to compare the relative importance of each communication mode in the learning process, and to quantify the effect of marketing communication in motivating consumer buzz. Methodologically, our modeling approach provides a rigorous treatment of endogeneity in quantifying the marginal return of WOM on sales by controlling for three potential confounding factors: marketing communication, consumers' perceived quality of the product, and unobserved product-specific effects. We apply the model to the video game software market with a unique dataset on consumers' WOM activities on over 200 online forums and discussion boards. Our results indicate that the proposed demand model outperforms benchmark models that do not incorporate direct WOM measures or do not incorporate quality learning. To summarize a few main findings:

(1) The *informative* effect: WOM is the primary mechanism through which consumers learn about the true quality of a video game. For an average game, WOM accounts for 80% of the quality learning in this market while publicity accounts for the remaining 20%. Advertising, on the other hand, contributes to consumers' learning only when the game represents a major innovation (as opposed to a minor update).

(2) The *persuasive* effect: WOM, advertising and media publicity each has a direct positive impact on video game sales. Publicity has an especially strong persuasive effect, meaning that the exact content of the publicity piece is unimportant in general (in a sense, "all publicity in good publicity"). The persuasive effect of WOM is much stronger for high quality products.

(3) Generating WOM (the *buzz* effect): Publicity has a substantial effect on generating WOM, Buzz marketing can be an effective tool of increasing long-term sales (the mean WOM elasticity is 0.15%); however, only higher-quality games can be expected to benefit from a boost in the amount of WOM. In other words, given the large informational role played by consumer WOM, engineering a buzz campaign for a mediocre product is unlikely to pay off financially.

Our study is subject to a number of limitations. For instance, the model does not explicitly capture competition. While a plausible solution is to cast the demand model in a multinomial discrete choice framework, it is unclear whether this approach is warranted in our empirical setting. First, consumers can (and often do) buy multiple video game titles in the same month. A fundamental therefore is what would be the competitive set? Luan and Sudhir (2009) studied the movie DVD market and found that there is negligible competition between simultaneously released DVD titles, and that the major competition comes from blockbuster films currently playing in theaters. Future work should investigate how consumers choose among a multitude of entertainment options so that we can better understand the nature of competition in the video game market. Second, given our focus on aggregate-level data and market-level effects, we do not explicitly consider the role of social network structure and opinion leadership in individuals' new product adoption behavior (Godes and Mayzlin 2008; Iyengar, Valente, and Van den Bulte 2009). Combining the macro- and micro-level WOM research might be a fruitful avenue of future research. For instance, instead of using an aggregate measure of WOM volume in our model, one could have multiple measures capturing the WOM activities in various social-network cohorts and model the dynamic evolution of WOM within and between these cohorts . Third, since our model assumes that WOM messages, on average, reflect the true quality of the product, identifying the marginal effect of WOM does not require detailed content analysis of each WOM message. This assumption can be relaxed in future research if one can link the linguistic, typographical, and sociological features of WOM messages and their authors to WOM recipients' perception of the product quality. Although machine-based sentiment analysis is still in the nascent stage of development, recent advances in this area (e.g., Nigam and Hurst 2004; Ghose and Ipeirotis 2008) point to a fertile avenue of future research.

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Table 1: Key Descriptive Statistics[a]

Variables	*Mean*	*Median*	*St.d.*	*Max.*	*Min.*
First month unit sales (000)	178.6	76.5	335.5	2695.2	2.4
First six-month unit sales (000)	376.7	204.0	503.9	4009.3	56.7
Retail price, first month ($)	59.4	60.0	18.3	169.0	20.0
Average retail price, first six months ($)	55.6	54.5	14.4	149.0	29.2
Magazine ad exposures, -1 to +2 month (millions)[b]	1.23	0.00	1.88	9.01	0
Number of discussion posts, -1 to +2 month[b]	10,677	1,417	45,340	529,732	28
Number of media coverages, -1 to +2 month[b]	15.6	16.0	7.6	50.0	0
Average reviewer rating (0-10)[c]	7.03	7.10	1.17	9.17	4.50

[a] Sample consists of 160 major console video games released between Jan. 2007 and March 2008.

[b] Total volumes from the month prior to game release date to two months after.

[e] Different rating scales are converted to a 10-point scale for comparison.

Table 2: Parameter Estimates for All Games (M1)

Demand Equation Estimates		
Intercept	0.465	(0.917)
N_WOM	0.013 **	(0.003)
N_AD	0.067 *	(0.034)
N_PBL	0.547 **	(0.036)
log(Price)	-1.093 **	(0.197)
Cumulative past adopters	3.887 **	(0.842)
Trend	-0.266 **	(0.017)
Mean quality perception (Q_{jt})	0.151 *	(0.091)
Uncertainty about quality (σ_{jt}^2)	-1.511 **	(0.307)
2nd Quarter[a]	0.387 **	(0.083)
3rd Quartera[a]	0.008	(0.064)
October[a]	-0.521 **	(0.081)
November[a]	0.151 *	(0.080)
December[a]	1.011 **	(0.074)
E-/ E10-rated[b]	0.341 **	(0.097)
T-rated[b]	0.210 **	(0.080)
Wii game[c]	-0.376 **	(0.075)
Xbox game[c]	-0.965 **	(0.058)
Action	0.079	(0.087)
Fighting	-0.066	(0.125)
Shooter	-0.148	(0.104)
Racing	-0.162	(0.104)
Sports	0.149 *	(0.089)
Family/Children	0.283 **	(0.105)
Adventure	-0.248 **	(0.099)
Role-playing (RPG)	0.228 *	(0.131)
Music/Dance	1.033 **	(0.160)

WOM Equation Estimates		
Intercept	1.280	(1.188)
Lagged N_WOM	0.372 **	(0.114)
N_AD	-0.027	(0.120)
N_PBL	0.782 **	(0.219)
Lagged sales	0.005 **	(0.002)
Mean quality perception (Q_{jt})	1.217 *	(0.693)
Uncertainty about quality (σ_{jt}^2)	-2.101 *	(1.201)
Trend	0.030	(0.038)
Action	-0.039	(0.204)
Fighting	0.083	(0.174)
Shooter	0.878 *	(0.475)
Racing	0.015	(0.287)
Sports	-0.049	(0.173)
Family/Children	0.085	(0.165)
Adventure	0.223	(0.191)
Role-playing (RPG)	0.214	(0.170)
Music/Dance	0.105	(0.398)

Signal Variance Estimates		
log(WOM variance)	2.415 **	(0.114)
log(AD variance)	12.652	(214.436)
log(PBL variance)	4.043 **	(0.373)

** p< .10, ** p< .05. Standard errors are in parenthesis.*

Notes: a. The excluded seasonal dummy is 1st Quarter.

b. The exluded base category is M- (Mature) rated games.

c. The excluded base category is PlayStation 3.

Table 3: Comparisons of Model Performance

	No WOM and No Learning (B1)		With WOM but No Learning (B2)		With WOM and Instant Learning (B3)		Proposed Model: Demand-side only (M2)	
Intercept	-2.151 **	(0.777)	-1.561 **	(0.791)	-1.557 **	(0.768)	0.516	(0.923)
N_WOM			0.046 **	(0.009)	0.025 **	(0.006)	0.013 **	(0.003)
N_AD	0.107 **	(0.037)	0.095 **	(0.037)	0.073 **	(0.034)	0.067 *	(0.034)
N_PBL	0.611 **	(0.035)	0.544 **	(0.036)	0.561 **	(0.035)	0.547 **	(0.036)
log(Price)	-0.711 **	(0.182)	-0.888 **	(0.188)	-0.860 **	(0.180)	-1.095 **	(0.197)
Cumulative past adopters	6.795 **	(0.409)	6.976 **	(0.572)	5.563 **	(0.580)	3.851 **	(0.850)
Trend	-0.232 **	(0.016)	-0.244 **	(0.016)	-0.247 **	(0.016)	-0.265 **	(0.017)
Mean quality perception					0.248 **	(0.035)	0.149	(0.094)
Uncertainty about quality							-1.537 **	(0.314)
E-/E10-rated	0.075	(0.089)	0.147 *	(0.089)	0.301 **	(0.085)	0.338 **	(0.097)
T-rated	-0.002	(0.072)	0.106	(0.074)	0.177 **	(0.069)	0.208 **	(0.080)
Wii game	-0.344 **	(0.074)	-0.362 **	(0.073)	-0.281 **	(0.079)	-0.378 **	(0.075)
Xbox game	-0.960 **	(0.059)	-0.939 **	(0.059)	-1.067 **	(0.061)	-0.965 **	(0.058)
log(WOM variance)							2.474 **	(0.087)
log(AD variance)							38.816	(288)
log(PBL variance)							4.158 **	(2.06)
MMSC-BIC	15.330		0.145		1.878		-11.91	

Table 4: Parameter Estimates for "Major Innovations" Only

Demand Equation Estimates

Intercept	0.581	(0.952)
N_WOM	0.040 **	(0.016)
N_AD	0.082 **	(0.039)
N_PBL	0.571 **	(0.042)
log(Price)	-1.122 **	(0.192)
Cumulative past adopters	3.820 **	(0.700)
Trend	-0.250 **	(0.017)
Mean quality perception (Q_{jt})	0.142 *	(0.080)
Uncertainty about quality (σ_{jt}^2)	-1.365 **	(0.378)
2nd Quarter	0.360 **	(0.082)
3rd Quartera	-0.065	(0.060)
October	-0.517 **	(0.085)
November[a]	- -	- -
December	0.976 **	(0.084)
E-/ E10-rated	0.226 **	(0.095)
T-rated	0.111	(0.080)
Wii game	-0.346 **	(0.080)
Xbox game	-1.128 **	(0.068)
Action	0.079	(0.086)
Fighting	-0.004	(0.133)
Shooter	-0.243 **	(0.107)
Racing	-0.004	(0.098)
Sports	-0.037	(0.091)
Family/Children	0.467 **	(0.106)
Adventure	-0.324 **	(0.101)
Role-playing (RPG)	0.313 **	(0.128)
Music/Dance	0.879 **	(0.180)

WOM Equation Estimates

Intercept	2.650 **	(0.597)
Lagged N_WOM	0.300 **	(0.086)
N_AD	0.015	(0.127)
N_PBL	0.781 **	(0.205)
Lagged sales	0.002 **	(0.001)
Mean quality perception (Q_{jt})	0.607 **	(0.193)
Uncertainty about quality (σ_{jt}^2)	-3.183 **	(0.527)
Trend	-0.003	(0.019)
Action	0.026	(0.128)
Fighting	-0.021	(0.147)
Shooter	0.124	(0.342)
Racing	0.195	(0.228)
Sports	0.077	(0.151)
Family/Children	0.067	(0.125)
Adventure	-0.068	(0.174)
Role-playing (RPG)	0.237	(0.155)
Music/Dance	0.520 **	(0.148)

Signal Variance Estimates

log(WOM variance)	3.202 **	(0.029)
log(AD variance)	3.363 **	(0.305)
log(PBL variance)	4.275 **	(0.266)

** p< .10, ** p< .05. Standard errors are in parenthesis.*

Note: a. No games were released in November in this subsample, so this parameter is unidentified.

Table 5: Short-Term Demand Elasticities of WOM, Advertising and Publicity (Starting from Month of Product Release)

Month	*1*	*2*	*3*	*4*
WOM				
All	0.113	0.087	0.034	0.008
Top Quality Quartile	0.374	0.271	0.127	0.104
Bottom Quality Quartile	0.054	0.047	0.026	0.019
Advertising				
All	0.016	0.041	0.026	0.007
Top Quality Quartile	0.015	0.040	0.021	0.013
Bottom Quality Quartile	0.016	0.037	0.023	0.004
Publicity				
All	1.391	1.029	0.443	0.117
Top Quality Quartile	1.507	1.022	0.394	0.074
Bottom Quality Quartile	1.093	0.837	0.540	0.188

Figures

Figure 1: Three Effects of Marketing Communications on Durable Goods Adoption

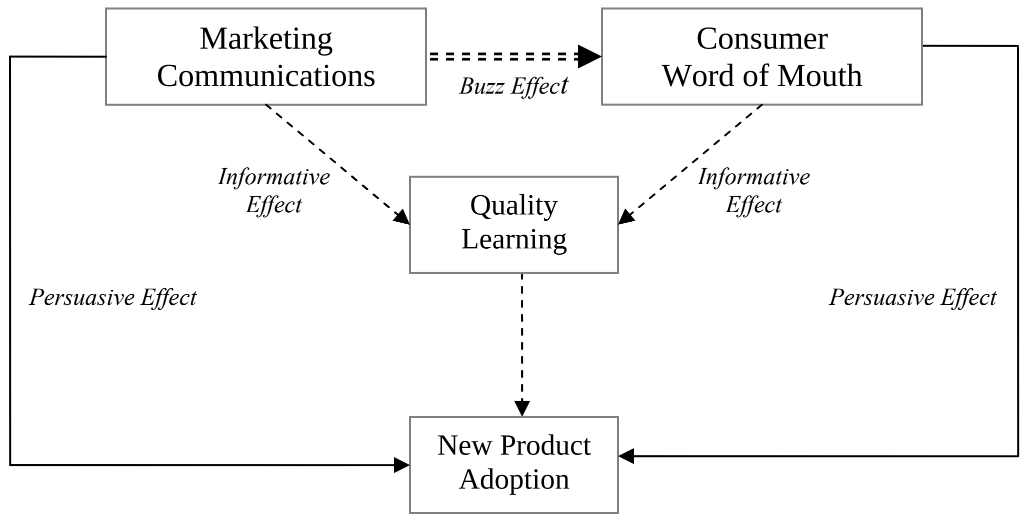


Figure 2: Sequence of Events during Period *t*

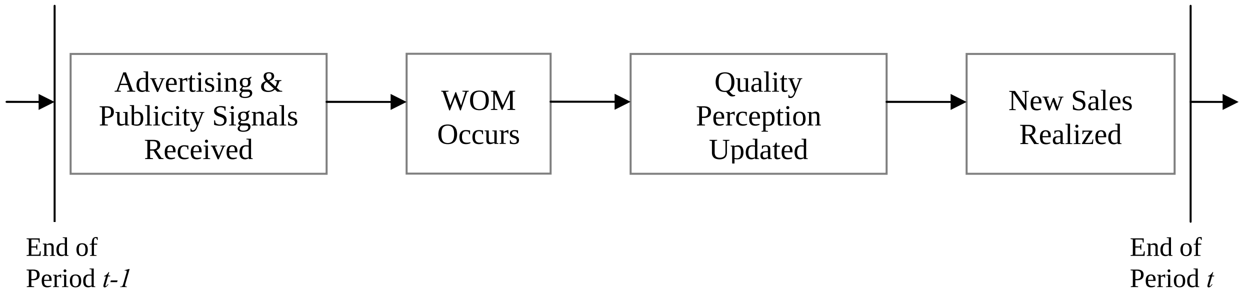


Figure 3: Total Installed Bases of Video Game Consoles during Sample Period

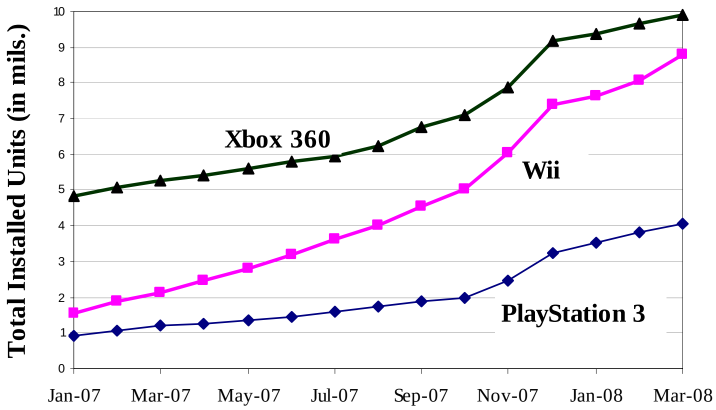


Figure 4: Examples of the Evolution of Perceived Quality (Q_{jt})

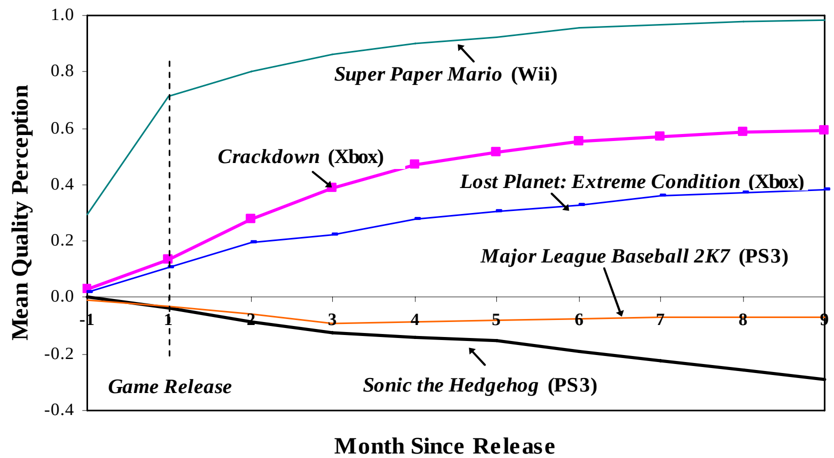


Figure 5: Examples of Percentage Reduction in Quality Uncertainty ($1-\sigma_{jt}^{2}/\sigma_{0}^{2}$)

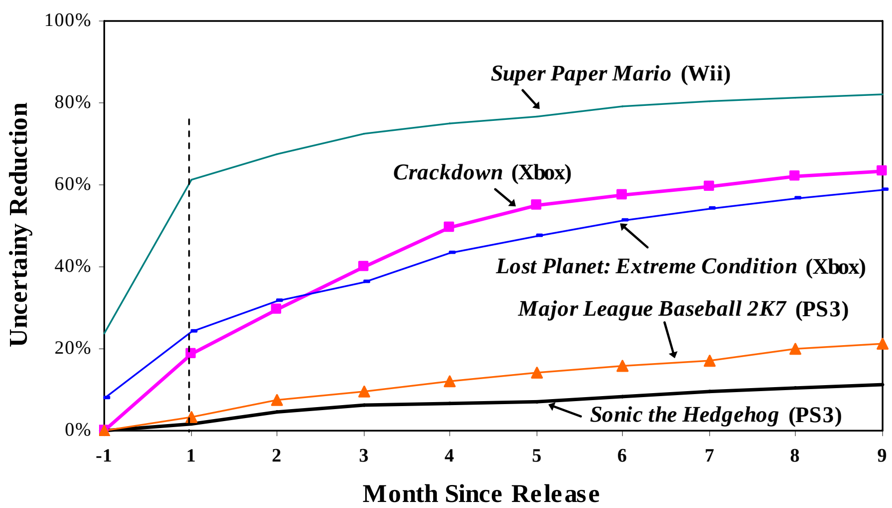
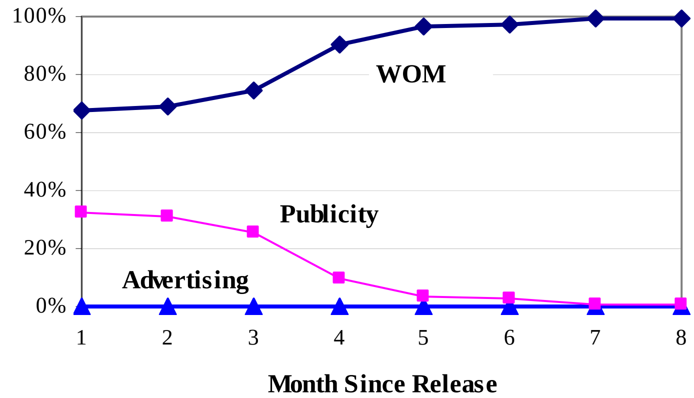


Figure 6: Mean Percentage Uncertainty Reduction by Information Sources

6(A). Percentage Uncertainty Reduction by Information Sources for All New Games



6(B). Percentage Uncertainty Reduction by Information Sources for Major Innovations Only

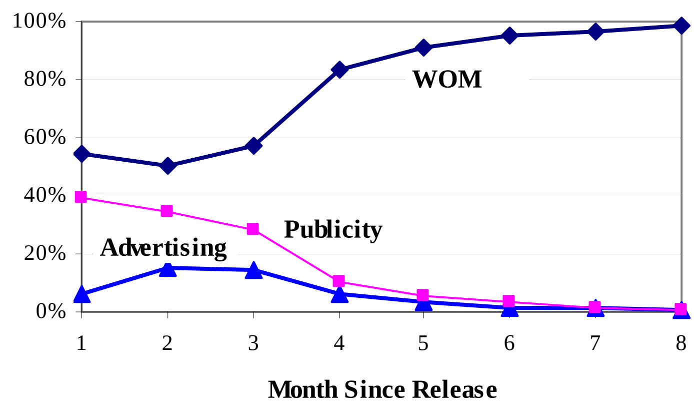


Figure 7: Mean WOM Elasticities for Higher- and Lower-Quality Video Games

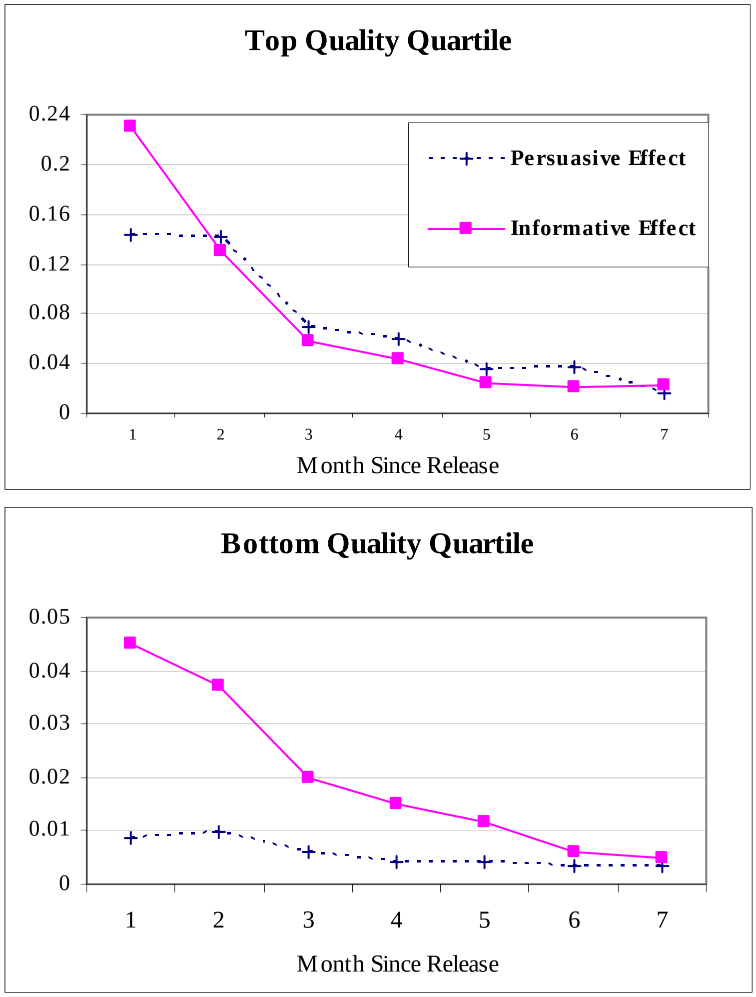
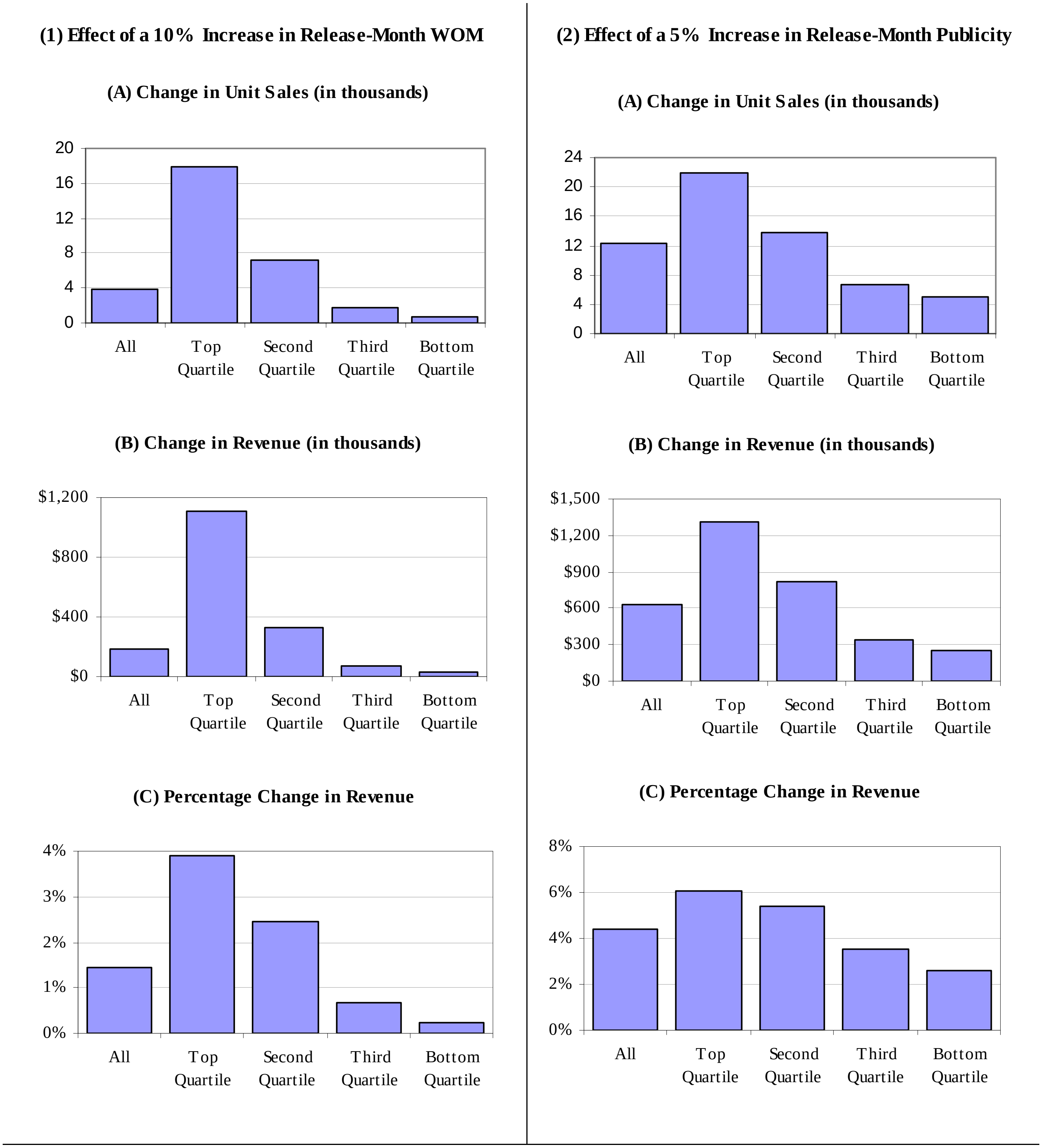


Figure 8: Long-Term Effects of a Policy Change



Web Appendix

Table A1: List of Publicity Sources

1UP.com
ActionTrip
Deeko.com
Empire Online
G4 / Tech TV
Game Almighty
Game Informer
Game Over Online
GameCritics.com
GameDaily
GamePro
GameSpot
GameSpy.com
GamesRadar [US]
GameTap
GameTrailers
GameZone Online
Gaming Age
IGN.com
Kikizo Games
Maxim Online
Nintendo World Report
Official Xbox Magazine
Operation Sports
Play Magazine
PS3 Advanced
RipTen
Stuff Magazine.com
TeamXbox
Total Video Games
UnderGroundOnline (UGO)
USA Today
Wii Advanced
Worth Playing
Xbox Advanced / Xbox 360 Advanced
Yahoo! Video Games

Table A2: Short-Term Demand Elasticities of WOM, Advertising and Publicity

(For Major Innovations Only)

Month	*1*	*2*	*3*	*4*
WOM				
All	0.144	0.122	0.056	0.027
Top Quality Quartile	0.479	0.365	0.180	0.140
Bottom Quality Quartile	0.050	0.051	0.030	0.022
Advertising				
All	0.030	0.073	0.050	0.011
Top Quality Quartile	0.030	0.060	0.037	0.019
Bottom Quality Quartile	0.014	0.057	0.039	0.006
Publicity				
All	1.390	1.060	0.446	0.127
Top Quality Quartile	1.656	1.092	0.434	0.174
Bottom Quality Quartile	1.144	1.010	0.634	0.130