THE PRODUCT LIFECYCLE FOR FAST-DECAY PRODUCTS: SALES RENEWAL IN THE US HOME VIDEO GAME MARKET

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Abstract

We examine the sales of hedonic products, specifically video games, over their product lifecycle. We generalize the commonly discussed two-stage framework, consisting of launch, with sales peak at or near product introduction, and decay, where sales decline monotonically. We add a third component, periodic sales renewal, to better describe the lifecycle of many products. Periodic sales renewals can be exogenous, event-driven such as a competitor action or seasonality or follow from endogenous actions such a price cut or an upgrade under the control of the manager. We augment the commonly applied exponential model with a Poisson jumps component to capture the incidence and magnitude of periodic sales renewals. Studying 2,396 video games on nine console platforms over an eight-year period, we find that periodic sales renewals are an important source of overall product sales and can be explained by events that relate to the focal product's actions and its competitive environment. Insights from this study can help marketers tailor their marketing activities over the product lifecycle.

Keywords: Product lifecycle, fast-decay product categories, video games.

THE PRODUCT LIFECYCLE FOR FAST-DECAY PRODUCTS: SALES RENEWAL IN THE US HOME VIDEO GAME MARKET

The dominant characterization of product sales in categories that include video games, movies, software, concert tickets, books, and fashion items is that sales peak around product launch and then decrease monotonically over time (Ainslie, Drèze, and Zufryden 2005; Binken and Stremersch 2009; Radas and Shugan 1998; Sawhney and Eliashberg 1996). Categories where the sales of individual products generally follow this pattern are referred to as "fast-decay" product categories. The commonly discussed product lifecycle for an individual product consists of two stages: the Launch Stage followed by the Decay Stage. It follows then that managers are recommended to focus their attention on affecting sales at launch, as well as the rate of sales decline following launch.

Sales may not always decline smoothly over the Decay Stage. Consider for example, Halo, one of the best-selling video games of all time (see Figure 1a). Its sales over time exhibit periodic sales renewals, or sales jumps, over and above a general monotone decay. This is a temporal sales pattern that occurs surprisingly frequently in hedonic products such as video games. A qualitative assessment of their magnitudes and periodicity suggests that these short periods of sales renewal may occur for reasons beyond simply seasonality.

[Insert Figure 1]

The need to develop a better understanding of the product lifecycle for fast-decay products was made clear in several interviews with managers working in these categories. These field interviews revealed a number of issues that guided our subsequent research. First, all managers stressed the importance of being able to develop accurate sales forecasts that could, for example, be used for meetings with distributors to guide their stocking levels. The dominant current approach was to identify a small number of "look alike" products that had been introduced earlier as a baseline and to then make adjustments based on the managers' qualitative assessment of differences for the focal product. For example, managers considered it important to account for differences in the current competitive situation at launch. They expressed a strong desire for a more systematic approach to sales forecasting. Second, while all stressed the importance of understanding both sales at launch and the subsequent decay rate, many managers cited sales jumps that occurred post-launch as a potential opportunity to grow overall sales. They knew these often occur around holiday periods but also observed that that wasn't always the case. Interestingly, their mental model was one of sales jumps overlaying a baseline, and not one of a series of peaks and troughs. A review of sales plots over time supports this view. Third, instances of similar competitive environments and marketing actions associated with very different sales outcomes (and vice-versa) created a source of frustration. Managers wondered if systematic investigation of sales drivers would provide insights into why this was the case. Challenged by such issues, marketers of fast-decay products are in need a comprehensive model that (1) retains the commonly held view of the importance of launch sales and sales decay while also accounting for the potential for sales increases through periodic sales jumps, and (2) includes variables that describe sales drivers for each of these components.

To date, researchers analyzing temporal patterns of sales in fast-decay products model the sales decay over the product lifecycle parsimoniously (Lehmann and Weinberg 2000; Moe and Fader 2001; Sawhney and Eliashberg 1996; Radas and Shugan 1998), and they treat deviations from a monotone decay in the Decay Stage as "seasonality" (see Figure 1b) or "noise" (see Figure 1c). The thesis of the current paper is that these deviations can collectively account for a nontrivial portion of a product's total unit sales and therefore represent opportunities for increased sales post-launch, making them managerially relevant. Unit sales are characterized by three components: sales at launch, a general monotone rate of decay, and sales renewal. We label the first two components as the "Launch Stage" and the "Decay Stage" and characterize "Sales Renewals" as a combination of the incidence or likelihood of a sales jump, as well as its magnitude when it occurs. We parameterize each component to account for product and situational factors such as the product's characteristics, marketing activity, and competitive environment, to name a few. Thus, the jump-decay model which we introduce below follows naturally from the three-component mental model of many managers who work in these categories: introduction, decay, and periodic sales renewals (or jumps).

We seek answers to two broad questions, which are important to understanding the lifecycle of fast-decay products. The first relates to the components of the product lifecycle and the second relates to the substantive drivers of sales in these categories.

- What can account for the frequent occurrence of periodic Sales Renewals in the Decay Stage? Which environmental and managerially controllable factors affect the incidence and magnitude of these sales spikes?
- Which environmental and managerially controllable factors are associated with the sales patterns (e.g., sales at launch, decay rate) of fast-decay products?

We make a number of contributions to the literature. First, we extend the product lifecycle of fast-decay products to account for periodic sales renewals as a key feature of fast-decay products. We model the entire sales path, explicitly accounting for both the characteristic monotonic sales decay and intermittent sales jumps. Our modeling framework, the jump-decay model, extends the commonly applied exponential model to include Poisson jumps by studying the information content in the variance of sales around the basic functional form. We then test our model using data on over 2,000 video game launches over an eight-year observation period.

Second, we identify the drivers of three key stages of the product lifecycle of fast-decay products: sales at launch, decay rate, and sales renewals in the form of sales jumps. Our results are consistent with the notion of the three-component product lifecycle and provide substantive insights into the relative effect of various sales drivers on each component. The ability to forecast the incidence and size of a sales jump or spike is a useful tool for account managers who work with channel partners to ensure sufficient stocking levels of products at a given point in time. While a parsimonious approach such as the exponential model is simpler, it understates the underlying sales decay rate in the presence of periodic sales jumps. Thus we develop critical managerial insights that can help not only to predict the occurrence of sales spikes but also to understand what factors drive these jumps.

Our findings clearly caution against indiscriminately ignoring sales jumps in the lifecycle of fast-decay products. Although obvious factors—seasonality and product quality—are important, we find that less salient factors contribute, as well. In the sample of video games we study, we find that expectations regarding future events related to the base console product affect both the incidence and size of sales jumps significantly. Moreover, the evolution of the installed hardware and whether a product is a sequel also significantly affect the occurrence of sales jumps.

The paper is organized as follows. We first introduce our institutional context, the US video game market, using it to motivate discussions of factors that affect the sales of individual games over time. We then introduce our modeling framework and contrast it with alternatives from the literature. We conclude with a discussion of our empirical results, managerial insights, and suggestions for future research.

Theoretical Development

We use the video games industry as the context to investigate the product lifecycle of fast-decay products. We provide a brief introduction of the nuances of the industry and in doing so introduce factors, environmental and managerially controllable, that affect product sales.

The video game industry has been examined by researchers in industrial economics, management engineering, organization management, and marketing, often for empirically investigating or extending Katz and Shapiro's (1985, 1986) ideas on indirect network effects, where the value of the base good (platform console) increases as more complementary goods (video games) become available (Clements and Ohashi 2005; Corts and Lederman 2009; Gretz 2010; Schilling 2003; Srinivasan and Venkataraman 2010). In a departure from the vast majority of these studies, where the primary interest is the platform console, our focus is on video games.

The physical product is a game cartridge containing software that runs off the platform console(s) produced by one manufacturer. We use the term "game" to describe this product, and it is our unit-of-analysis.[1] Competitors are operationalized as competing platform manufacturers; cannibalization occurs when sales are lost across platforms of the same manufacturer.

2.1 Institutional Context: The US Video Game Industry

The video games industry is the economic sector involved with the development, marketing, and sale of video games and related hardware. The Americas account for over 40% of the global game console market's revenue. We discuss some key nuances of this industry that may have significant impact on the product lifecycle of new products. Figure 2 presents our conceptual framework.

[Insert Figure 2]

[1] Some third-party developers publish versions of the same software for multiple platform consoles (e.g., Madden NFL 13 for Xbox 360, Madden NFL 13 for Nintendo Wii, Madden NFL 13 for Playstation 3). Each is a distinct product with its own lifecycle.

Innovation

The video games industry demonstrates high levels of innovation, and firms compete on the basis of technological superiority. Firms make large investments in R&D to pioneer unique capabilities in hardware consoles and new features in games. Firms also pursue active strategies to pre-announce new product launches and upgrades. Hardware console manufacturers pre-announce launch dates of next-generation consoles with higher technical capabilities months ahead of their actual release dates. For example, Sony unveiled the PlayStation 3 console on May 2005 during the E3 2005 conference, much ahead of the actual launch in November 2006. These pre-announcements provide early information of innovative features to customers or distributors and increase demand for new games based on these consoles. Hardware console manufacturers also pre-announce upgrades to old consoles that offer both performance improvements (e.g., new ports and access to online gaming) and cosmetic changes (e.g., more colors and new accessories). For example, Sony launched the Slimline and PSX upgrades of PlayStation 2 to complement the original case version of PlayStation. The upgrades offered higher storage capacity and faster processing speeds than the earlier versions. These hardware pre-announcements may increase the sales of individual video games as consumers time their purchase decisions with these launches.

Innovations related directly to a focal console owned by a consumer may influence him/her. However, innovations related indirectly to the focal console—for example, those related to other consoles offered by the same manufacturer (cannibalization effects, as in the impact of pre-announcement of an Xbox upgrade on sales of a Nintendo game) or those offered by competitor manufacturers (competitor effects, as in the impact on sales of a PS2 game with pre-announcement of a PS3 launch)—may also affect consumer decisions. We account for all three effects.

High Brand Loyalty

The hardware console market is almost exclusively dominated by Nintendo, Sony, and Microsoft. Of the three firms, Nintendo was the first to enter this industry and commands the lion's share of the market worldwide. Sony subsequently launched many innovative and highly successful products (such as the PlayStation series) and acquired the second largest share. Microsoft, a relatively new entrant to this industry, has taken away a significant market share from both firms through aggressive new product development and marketing strategies.

Consumers demonstrate high levels of brand loyalty in this industry, and there are considerable switching costs associated with high hardware and learning costs. Accordingly, we observe that even though the ownership of multiple consoles across platforms is growing, consumers continue to exhibit high levels of loyalty to one platform. Most major game developers adopt a cross-platform strategy and make games compatible across consoles. However, manufacturers also fund development projects for games customized to their consoles, thereby yielding higher performance on the focal console. We therefore expect the product lifecycles of individual video games to differ across these consoles.

Seasonality

Sales in this industry exhibit high levels of seasonal behavior in both consumers and firms. Hedonic or fast-decay products are often launched just before or during holiday periods to coincide with higher consumer spending both for self-consumption and gift-giving during holiday periods. As a result, a clustering of various events arises during holiday periods: gift-giving, new launches, upgrades, and price promotions. Holiday periods therefore have the potential to affect the entire product lifecycle: sales at launch, rate of decay, and sales renewal.

Product Characteristics

Quality information: Product quality information is an important factor affecting both the sales at launch and the rate of decay. In this industry, consumers have relatively easy access to a number of well-accepted sources for product quality information. Moreover, consumers themselves rate new games, and various agencies (e.g., gamerankings.com; metacritic.com) aggregate these reviews. The availability of product reviews decreases the uncertainty surrounding the quality of a new game and guides customers in their purchase decisions. We expect that a high-quality product may experience higher sales at launch, a slower rate of decay, and higher sales renewal than a low-quality product. In theory, quality information can vary over time as its value is updated based on customer experiences post-launch, but in reality, quality information changes very little over time and is effectively time-invariant.

Franchise: Video game publishers often choose to develop franchises of popular characters and settings. Such franchises are attractive to both creators and publishers alike because developing a story with known popularity poses lesser risk than developing a story with new, untested characters and settings. Prior literature studying movies suggests that sequels have higher box-office sales than the prequels (Sawhney and Eliashberg 1996). We expect sequels to experience higher sales at launch. The higher attractiveness of sequels may also result in pulling the total demand earlier in time as eager audiences rush to purchase the game soon after launch, resulting in a higher rate of decay and lower sales renewal than non-sequels (Luan and Sudhir 2010).

Genre: Different genres in the video games market represent different consumer segments. Some genres, such as sports and action games, are more seasonal than others. For example, FIFA Soccer, a series of video games released annually by Electronic Arts, is launched in conjunction with the football season. The demand for such games is high at launch, and typically decays quickly after that.

Installed Hardware Base

Most fast-decay product categories comprise complementary and interdependent products (Binken and Stremersch 2009; Katz and Shapiro 1986). For example, a specific video game, a complement good, can be used only with a specific video game platform console, the base good. Thus the size of the installed base good affects the sales of a complement good. We expect games with a larger installed base to experience higher sales at launch. More popular platforms, however, may also enjoy a higher number of new games launched, increasing the competition and hurting sales. Games with a larger installed base may consequently have a faster rate of decay and lower sales renewal.

Marketing

We analyze three main marketing activities common in this industry: holiday launches, console price promotions, and game price promotions. Firms routinely make announcements of new product launches and/or console price promotions closer to the holiday period; they also routinely announce price promotions for individual video games.

Holiday Launches: Manufacturers traditionally align the launch of new video games with the holiday period. Consumers increase the rate of shopping during these months, and the sales at launch may therefore be higher for games launched closer to holidays than for games launched during other times. Holiday sales are also usually followed by periods of lower shopping activity that can result in a faster rate of decay for games launched in this period. As a result, we expect that games launched during holidays will experience higher sales at launch and higher sales renewal but a faster rate of decay than games launched at other times.

Console Price Promotions: Hardware console manufacturers often announce price cuts of older generation consoles when new generation consoles are launched. Price cuts may also occur in response to waning market demand, competitor actions, improved manufacturing processes, or aging systems. For example, Sony has reduced the price of PlayStation 2 more than six times since its introduction in 2000 (from $299 to $199, $179, $149, $129, and $99). While console price promotions are frequent, price patterns differ across consoles, rendering the timing of a price discount unpredictable. The pre-announcement of price cuts may influence all three components of the product lifecycle: sales at launch, rate of decline, and sales renewals.

Game Price Promotions: Video games undergo frequent and successive price discounts after their initial launch. These events spur sales spikes as a new segment of more price-sensitive consumers rush to purchase these games when price promotions are announced.

In addition to accounting for effects related to innovation, we also account for the three effects of price promotions: those related directly to the focal console (direct effects), those related to other consoles offered by the same manufacturer (cannibalization effects), and those related to offers by competitor manufacturers (competitor effects).

Method

We develop a modeling framework that combines the three major components of the lifecycle of fast-decay products: Launch Stage, Decay Stage, and Sales Renewals. We use two measures, cross-sectional forecast and time-series forecast, to compare the predictive ability of this approach to that of four alternative models: the exponential model, generalized gamma model, generalized bass model, and semiparametric proportional hazard model.

Jump-Decay Model (JDM)

We model the sales patterns of video games as periodic sales renewals in the form of sales jumps punctuating a gradual decay in sales after launch, in line with the manager's mental model and with empirically observed phenomena.

Sales Decay Sub-Model

The first part consists of an exponential model. We model the decay in sales for game *g* in time *t* as follows:

(1) $$Decay_{g,t} = e^{\beta_{1,g}+t*\beta_{2,g}+\varepsilon_{g,t}}$$

where $\varepsilon_{g,t} \sim N(0, \sigma^2)$, *g*=1,...,G is the number of games and *t*=1,...,T_g is the total number of time periods for each game g. $\beta_{1,g}$ captures the sales level of the game at launch, and $t * \beta_{2,g}$ captures the speed of sales decay. Both parameters$\beta_{1,g}$, the sales at launch, and$\beta_{2,g}$, the decay rate, can be parameterized as functions of game-specific characteristics V_g .

(2) $$\beta_{i,g} = V'_{i,g}\bar{\beta} + v_g,$$

where $\beta_g = (\beta_{1,g}, \beta_{2,g})', v_g \sim N(0, \Sigma_\beta)$, *i*=1, 2.

In empirical application we used the same set of game-specific variables in Wg (from equation 5) as in *Vi*,*g*, except the genre variables (we tested a version of the model with genre variables and they are not significant, therefore we dropped them for parsimony). We include the following game-specific variables: quality, sequel, holiday launch, installed base, brands, and genre. We also include indicator variables to capture any systematic differences across years. The variables affecting the sales at launch and decay rate are game-specific and do not change over time.

Sales Jump Sub-Model

We model both the probability and magnitude of a sales jump for game g in time *t*. We model both the probability and size of sales jump as follows:

(3) $$Jump_{g,t} = e^{k_g J_{g,t}}$$

The sales spikes $J_{g,t}$ occur intermittently, driven by variables described above as a time-inhomogeneous Poisson process. The jumps $J_{g,t}$ are game-specific and the number of jumps can change over time.

(4) $$J_{g,t} \sim Poisson(\exp(Z'_{g,t}\gamma)).$$

J_{gt} captures the jump probability and size variation over time. The expected number of jumps for game g in time *t* is given by $\exp(Z'_{g,t}\gamma)$, where $Z_{g,t}$ are independent variables that affect spike probability. However, the sales jumps differ both within a game over time and across games. $k_g$captures the jump size variation across games and $J_{g,t}$ captures the jump probability and size variation over time. These two components cannot both vary over time, due to identification reasons. We allow parameters k_g measuring each jump size to be a function of game specific characteristics W_g as follows:

(5) $$k_g = W_g{}'\Delta + u_g, \text{ where } u_g \sim N(0, \sigma_k^2)$$

All the variables affecting the jump size are also game-specific and do not change over time. But the variables affecting jump probability are time-varying, because the jump probability is also time-varying. We include indicator variables to capture any systematic differences across years. Note that if a variable does not change over time, it still affects a sales jump through its effect on the magnitude of the jump.

Our final jump-decay model combines the two sub-models to capture the sales for game g in time *t* as follows:

(6) $$S_{g,t} = Decay_{g,t} \times Jump_{g,t} = e^{\beta_{1,g}+t*\beta_{2,g}+\varepsilon_{g,t}} \cdot e^{k_g J_{g,t}}$$

We estimate the parameters using a Bayesian method (Rossi, Allenby, and McCulloch 2005). The posterior distribution and estimation details are included in Web Appendix A. This approach has four advantages. First, it models the empirically observed phenomenon well, taking into account the fast-decay feature of these products while incorporating variations in sales. Given that a Poisson function can generate more than one jump per period, we can capture both the frequency and the magnitude of sales jumps. Second, the model is not limited to accounting for variations in sales attributed solely to seasonality but also allows inclusion of both time-varying and time-invariant variables that account for sales in the product's lifecycle. The game-specific hyperparameters β_g and k_g and the independent variables V_g and W_g allow the model to capture fluctuations in sales across games. Third, the model is easy to estimate and allows for managerially actionable variables such as price promotions, pre-announcements, and the impact of competitor actions. Fourth, the model has a superior predictive accuracy over comparable models, as we will show in the section below.

Comparative Models

Table 1 qualitatively compares all the models on four parameters: the ability to (1) include time varying variables, (2) account for seasonality in sales, (3) include out-of-sample forecasts, and (4) include variables that describe the drivers of sales jumps. Some models employ an event-centric approach and model key events in the marketplace or consumer decision-making through the hazard model framework (see Figure 1d); other models are intrinsically product lifecycle–centric and model sales after accounting for seasonality. As Table 1 shows, the jump-decay model is the only model that allows us to analyze the drivers of sales jumps.

[Insert Table 1]

Exponential Model (XM)

The exponential model is an intuitive model for the generally declining sales pattern in fast-decay products. This model was used by Lehmann and Weinberg (2000) to describe the sales patterns in movie theatre releases and subsequent video store sales. It was also used by Moe and Fader (2001) as the foundation of their multi-segment sales model of music CD sales.

For simplicity and comparability across models, we assume a single segment in each video game market while allowing different games to have different parameter estimates.

According to the exponential model, the sales for game *g* in time *t* is given by

$$S_{g,t} = m_g * e^{-\lambda_g t_g} + \varepsilon_{g,t} \tag{7}$$

where m_g is a parameter representing the initial value of the exponential sales curve, λ_g is the rate of decay in sales for game g, and t_g is number of months since the launch of game g. $\varepsilon_{g,t}$ is an *i.i.d.* random error across games.

We estimate parameters m_g and λ_g with a nonlinear least square procedure. For starting values of m_g, we tried both first-month sales and maximum sales over a game's lifetime. These two starting values result in similar parameter estimates for m_g. We used .1 as starting value of λ_g. Note that the XM model in the presence of jumps will typically predict a much shallower decay rate than actual because the curve is chasing sales spikes; it is therefore important to separate the decay from the sales spikes.

Generalized Gamma Model (GGM)

The generalized gamma model, advanced by Sawhney and Eliashberg (1996) to forecast the box-office revenue of movies, models the time-to-adopt as the summation of a movie's time-to-decide and time-to-watch. Each decision is modeled as a separate exponential process. The individual decisions are then aggregated to the population level. The convolution of the two independent exponential processes results in the following cumulative sales for game g in time t:

$$(8) \qquad E(N_{g,t}) = \frac{N_g}{\lambda_g - \gamma_g}\left[\left(\lambda_g - \gamma_g\right) + \gamma_g e^{-\lambda_g t_g} - \lambda_g e^{-\gamma_g t_g}\right]$$

where $N_{g,t}$ is cumulative sales of game g in time t, and λ_g and γ_g are respectively the time-to-decide and time-to-act parameters in the generalized gamma function. N_g is the total potential market size for game g, while t_g represents the number of months since game g's release. We compute the sales in each time t as

$$(9) \qquad S_{g,t} = N_{g,t} - N_{g,t-1}.$$

Following Sawhney and Eliashberg (1996), we estimate the model parameters using the nonlinear least squares procedure. We use 90% of the real cumulative sales of the focal game during its lifetime as the starting values for N_g, 2 for γ_g and 1 for λ_g.

Generalized Bass Model (GBM)

The generalized Bass Model is widely used to model new product adoptions (Bass, Krishnan, and Jain, 1994; Bass, Jain, and Krishnan 2000). Besides the GBM, the Proportional Hazard Bass Model also incorporates independent explanatory variables and was used as a comparison model in Chintagunta, Nair, and Sukumar (2009). Bass, Jain, and Krishnan (2000) showed that these two versions of Bass Model give similar model fit and parameter estimates.

According to this model, the cumulative sales of game g in time t is

$$(10) \qquad N_{g,t} = \frac{1 - e^{\left[-\left(X_g(t) - X_g(0)\right)\left(p_g + q_g\right)\right]}}{\left(\frac{q_g}{p_g}\right) . e^{\left[-\left(X_g(t) - X_g(0)\right)\left(p_g + q_g\right)\right]} + 1} m_g$$

where $N_{g,t}$ represents the cumulative sales of game g in time *t*, and p_g, q_g and m_g are the parameters of the Bass Model. $X_g(t)$ represents the cumulative marketing effort (Bass, Krishnan, and Jain 1994), with functional form as follows:

$$(11) \qquad X_g = t_g + \frac{\ln(Pr_{g,t})}{\ln(Pr_{g,0})}\beta_{g,1} + \ln(Console\ Price\ Index_{g,t})\,\beta_{g,2} + \sum_{\tau=0}^{t_g}\left(\sum_{l=1}^{12}\gamma_{g,l}D_{g,l,\tau} + \sum_{k=1}^{5}\lambda_{g,k}E_{g,k,\tau}\right)$$

where t_g is the time (months) since game g's launch; $Pr_{g,t}$ is the price level of game g in time *t*; and $Pr_{g,0}$ is the launch price for game g. $Console\ Price\ Index_{g,t}$ is a price index for the game console that the game is played on. It is calculated as weighted price of console in period *t* (using sales of each model of the console as weight) divided by the launch price of the console. The last part has two components. The first, $\sum_{\tau=0}^{t_g}\sum_{l=1}^{12}\gamma_{g,l}D_{g,l,\tau}$, , captures cumulative seasonality effect on sales. $D_{g,l,\tau}$ represents the monthly dummies, which equal 1 when a month number equals l, and 0 otherwise. The second, $\sum_{\tau=0}^{t_g}(\sum_{k=1}^{5}\lambda_{g,k}E_{g,k,\tau})$, captures the cumulative effect of announcements related to price cuts or upgrades of various console on sales. $E_{g,k,\tau}$ are the dummies, which equal 1 when an event is announced, and 0 otherwise. We compute the sales in each time *t* as

$$(12) \qquad S_{g,t} = N_{g,t} - N_{g,t-1}$$

We estimate the Generalized Bass Model with the nonlinear least squares method proposed by Srinivasan and Mason (1986), as suggested by Bass, Krishnan, and Jain (1994).

Semiparametric Proportional Hazard Model (SPPH)

We compare our model to the semiparametric proportional hazard model for video game console sales developed by Chintagunta, Nair, and Sukumar (2009). This model is designed for sales patterns with obvious "spikes." It is derived from the proportional hazard formulation of the Bass Model (Bass, Jain, and Krishnan 2000) while allowing for semiparametric parameters in the baseline hazard function. The sales for game g in time *t* is given by

$$S_{g,t} = (m_g - N_{g,t-1})[1 - e^{(-e^{(\alpha_{g,\tau} + W_{g,t}\gamma_g + \varepsilon_{g,t})})}] \tag{13}$$

where $S_{g,t}$ is the sales of game g in time *t*; $N_{g,t-1}$ is the cumulative sales of game g in time *t-1*; and m_g is the market potential for game g. $\alpha_{g,\tau}$ is the semiparametric parameter, which is both game-specific and time-specific. $\varepsilon_{g,t}$ represents the unobserved drivers of sales in time *t*. Using the same assumption as Chintagunta, Nair, and Sukumar (2009) that $\alpha_{g,\tau}$ takes semi-annual values, we use $\alpha_{j,1}$ for the first 6 months since game launch, $\alpha_{j,2}$ for months 7-12, and so on. $W_{j,t}$ represents independent variables that may influence video game sales. We use the same available time-varying variables as in our model, including game price, console price index, and console events dummies. We also include a seasonality variable to capture the November-December holiday season, as suggested in Chintagunta, Nair, and Sukumar (2009). When there are fewer than 12 months of sales observations for a particular game, a seasonality variable is unidentifiable and therefore dropped. When there is no console price change during the entire life span of a game, console price index cannot be identified and is dropped.

Chintagunta, Nair, and Sukumar's model (2009) differs from ours in that they estimate consoles sales whereas we estimate game sales. While the two models are certainly comparable, some of the specifics differ. First, we include the same time-varying variables (game price, seasonality, console price index, and console event indicator variables) as in the jump-decay model to allow for comparison, while Chintagunta, Nair, and Sukumar (2009) use video game console price, seasonality, and number of game titles. Second, the parameters γ_j in our model are game-specific while the variables in Chintagunta, Nair, and Sukumar's model (2009) are common across consoles. We made these modifications to the original model to ensure consistency with all the other models.

In following the procedure used by Chintagunta, Nair, and Sukumar (2009) to estimate the model, we (1) assume an initial value for m_j ; (2) estimate $\alpha_{j,\tau}$ *and* γ_j using OLS; (3) update m_j using nonlinear least squares method; and (4) iterate between steps (2) and (3) until the value of m_j meets prespecified criteria for convergence. The starting value of m_j is taken as 105% of the real cumulative lifetime sales of the game to ensure the nonlinear least squares' convergence.

Endogeneity of Price Promotions

Price endogeneity can be a concern when modeling sales, but we believe this concern is not significant in this specific case. Hernandez-Mireles, Fok, and Hans Franses (2011) showed from a study of 1,195 video games that past sales are not primary triggers of price changes. Nair (2007) also showed that video game publishers do not price video games optimally with respect to demand. We therefore assume that the price changes are exogenous, and we do not control for endogeneity. If this assumption is weakened, our price estimate would show more price elasticity than in reality, as illustrated in Chintagunta, Nair, and Sukumar (2009), who model console sales and address the endogeneity problem by introducing instruments. Since our paper's main focus is the sales jumps in games and not consoles, we use price just as a control variable.

We do not consider event announcements to be endogenous, because they are made by console manufactures, not the game publishers. These two are not necessarily the same agents and are unlikely to collude to profit maximize towards the same goals.

Model Comparison and Goodness of Fit Measures

In their standard forms, two of the comparative models (exponential and generalized gamma models) do not directly incorporate covariates in their estimations (see Table 1). In order to provide a comparison with the other approaches, which do allow for the inclusion of covariates, we develop modified versions of these methods for the out-of-sample forecast. These new versions incorporate all the covariates used for the jump-decay model. The semiparametric proportional hazard model is not designed for an out-of-sample forecast, since the key parameters are console and time-specific (Chintagunta, Nair, and Sukumar 2009). Therefore we do not include this model in the out-of-sample forecast comparison. In addition to the cross-section type of out-of-sample forecast, we also use the early-stage sales information on a game to help improve the forecast on later stages (we call this “time-series forecast”). We explain how exactly we make these predictions and forecasts in Web Appendix B.

Data

We study a sample of 5650 video games launched between January 2004 and November 2011. We explain four specific problems we encountered and the rules we used to resolve them to arrive at our analysis sample. First, we dropped games that were launched before the start of the observation period. Second, we dropped games that were launched after December 2010, because of few observations. Third, based on discussions with managers working in the video game industry, we dropped games where total sales were less than 100,000 units, as the marketing, distribution, and target customer for these games tend to be very different compared to the games we study. Fourth, we dropped games that were in the market for less than 6 months, regardless of their launch date. The final sample after these rules were applied comprised 2396 games from nine console platforms.

For each game we collected data on the launch date, publisher, genre, and platform. We collected the quality ranking data for each game from the website GameRankings.com. We control for the following genres: sports, adventure, action, party, simulation, puzzles, and fitness.

We used multiple sources, including Factiva, Lexis-Nexis, and company websites to identify the date a firm made the first announcement of a launch or upgrade of a console, or of a price cut.

We control for the recent-release effect, because games launched in 2009 and 2010 have a shorter sales record in our dataset (our observation window ends November 2011) but much higher average sales and average prices than the earlier games in our sample. To prevent this from distorting our results, we include indictor variables for games released in 2009 and 2010.

Empirical Analysis

We first present descriptive statistics of the data. Then we present the results of the model estimation and a comparison of the predictive accuracy of all models.

Descriptive Statistics

Consistent with prior literature, we find that a small proportion of games accounts for the largest share of total sales of all games. The dataset includes 835 games from Nintendo, 1115 games from Sony, and 446 games from Microsoft. A substantial portion (42%) of these games was launched during the holiday season. Over the observation period, there was a consistent increase in installed units of consoles across most consoles (which is related to the market potential for a game). Across the sample, the installed base is largest for Nintendo's Game Boy Advanced (GBA) and Sony's PlayStation 2 (PS2), but the rate of growth is higher for Nintendo's Dual Screen (NDS) and Sony's PlayStation Portable (PSP). Over the same period, almost all platforms also had price cuts, with some platforms (e.g., Microsoft Xbox) offering more aggressive price cuts than other platforms (e.g., Sony PlayStation).

Drivers of Sales at Launch and Exponential Decay

Table 2 presents the results. As expected, high quality games have higher sales at launch. The rate of sales decay, however, is unaffected by the quality. Sequels benefit from both higher sales at launch and a faster rate of decay. Contrary to our expectation, the results suggest that, in general, games launched during holidays experience neither higher sales at launch nor a faster rate of decay than games launched at other times. Accordingly, after controlling for other factors, the holiday month launch does not have any additional effect on these variables. Nor did we find that games launched on platforms with a larger installed base benefit from either higher sales at launch or a slower decay rate. The game console manufacturer dummies, however, yield an interesting insight. We find that in comparison to games from Sony, games from Nintendo have a slower decay rate, but the sales at launch are not different. In contrast, games from Microsoft generally have lower sales at launch, but the decay rate is not different. We explore this finding later by comparing the differences in the portfolio of genres from these manufacturers. The results also suggest differences across genres.[2] As expected, sports games have a higher decay rate because of the more seasonal nature of this genre. On the other hand, almost all other genres—adventure, action, party, simulation, puzzles, and fitness—have higher sales at launch but no difference in the decay rate in comparison to the ”driving,” “strategy,” and “simulation” genres.

Drivers of Sales Jumps

We first discuss the factors that affect the magnitude of sales jumps and then the factors that affect their incidence (see Table 2).

The results on the magnitude of sales jumps suggest that higher quality games have smaller sales jumps than lower quality games, a finding in line with information economics theory. Higher quality games are also more advertised and have greater word-of-mouth, which

[2] We did a pre-test by including dummies for all 15 genres, which are “sports,” “adventure,” “platformer,” “shooter,” “action,” “fighting,” “driving,” “party,” “music,” “strategy,” “life simulator,” “role play,” “simulation,” “puzzle brain,” and “fitness.” Then we combined some similar genres, such as “action,” “fighting,” “shooter,” “party,” and “music” into fewer genres, and left the other nonsignificant genres such as “driving,” ”strategy,” and “simulation” as baseline.

reduces the uncertainty surrounding product quality. As a result, more of the potential demand is converted to actual sales closer to launch, reducing the potential for sales jumps post-launch. We find that sequels have larger sales jumps than non-sequels, as later versions (sequels) refresh the demand for older versions, which then experience larger sales jumps. We find that neither the holiday launches nor the installed base seems to affect the size of sales jumps. Nintendo games have larger sales jumps in comparison to games from Sony, while games from Microsoft have smaller sales jumps.

The results on the timing of sales jumps suggest that a drop in console price decreases the probability of a sales jump. We believe that this occurs because the console price trends downward, often accompanied by a console sales decay. As a console ages, better alternatives in the form of new launches and upgrades are introduced in the market. This results in a reduction of the consumer base for the old console over time. For example, the sales of PlayStation decreased when its successor console, the PS2, was launched. It seems that though consumers who wait to buy a game until a console becomes cheaper are a minority. Instead most consumers take the price drop as a sign that the console is becoming obsolete, and are reluctant to buy games for the old console. In other words, the price signaling effect dominates the usual price cut effect of a complementary good. The sign of the price console index is verified by parameter estimates from the semiparametric model, which is also positive.

Price promotions of consoles by competitors inhibit the occurrence of sales jumps, but less than the price promotions of other compatible consoles by the same manufacturer. This suggests that due to the lock-in effects of the consoles, consumers are more sensitive to price promotions related to their own console than to those of other consoles. Many consumers own more than one console and may not upgrade regularly when new versions launch. For example, if a consumer owns both an Xbox and a PlayStation console and Microsoft announces a price cut on the Xbox360, the results suggest that as the Xbox360 becomes more attractive, consumers will reduce their purchase of older games compatible with Xbox. A similar effect is observed if the announcement concerns a competitor console, e.g., Wii, and consumers are encouraged to resist the price reduction of current games and adopt the new console (and its games).

Similar effects can be observed regarding the announcements of console upgrades and new console launches. An upgrade or new launch of a competitor console negatively affects the occurrence of sales jumps, but less so than the announcements on base consoles or on other compatible consoles from the same manufacturer. The reason for this negative impact on sales of existing games is that new consoles bring in increased technical capabilities and better games, leading consumers to gravitate towards newer games. Each new upgrade, therefore, can increase sales at the launch of new games but has a negative impact on the occurrence of sales jumps of older games.

We capture the impact of seasonality through monthly dummies. The results suggest that the probability of a sales jump or spike differs substantially across months. In comparison to January, the reference month, sales are comparatively flat until March, after which there is a significant decay for two months (April-May). Sales pick up again during the summer holiday season (June) before hitting another lean period (July to October). Sales peak in November and December, most plausibly because of increased gift-giving and holiday spending. We also compare these estimates with average sales per month, and the two patterns are similar.

Comparison of Predictive Accuracy

We compare the within-sample fit and the cross-section and time-series predictive accuracy of all models using median absolute percentage errors (APE). We use the median for comparison because it is not affected by extreme values. We also report the mean of APEs for first 36 months of observations after removing 10% of outliers. For models whose performance is close, we conduct t-tests on the two models' APE time series to decide whether the differences are significant.

Within-Sample Fit Statistics

Using the several comparison models, we generated the within-sample fit. Figure 3a plots the median APE across all games for within-sample fit. The jump-decay (JD) model has the lowest median APE using both metrics, mean and median. We find that within-sample fit for the semiparametric proportional hazard model (0.60) (see Table 3) is slightly worse for games sales than the .496 reported in Chintagunta, Nair, and Sukumar (2009) on console sales. To ensure that we replicate their method well, we apply our code to console sales data of PlayStation 3 over a 65-month period. The Mean Absolute Percentage Error (MAPE) from PlayStation 3 console sales is around 40%, similar to that found by Chintagunta, Nair, and Sukumar (2009). This also suggests that the semiparametric proportional hazard model is more suitable for sales patterns similar to console sales (where the baseline sales is relatively unchanged over time, with periodic "spikes") and less so for sales patterns similar to video game sales (where the baseline sales decay rapidly).

[Insert Table 3, Figure 3]

Cross-Section Forecasts

Figure 3b plots the median APE across all games for cross-section forecasts. Our model is superior in median (but not mean) APE for cross-section forecasts (see Table 3). The jump-decay model has much lower median APE (.74) than all the other alternative models in the first 3 years. The difference is significant at 5% level for pair comparison. However, the Generalized

Bass Model (GBM) has a lower mean APE. This suggests that the jump-decay model performs better in normal cases but could occasionally generate larger errors than the GBM.

Time-Series Forecasts

Figure 3c plots the median APE across all games for time-series forecasts. Our model is superior in both the mean and median APE (see Table 3), and the difference, based on a t-test, is significant. Compared with the cross-section forecast, the reduction in APE is significant for most of the models for periods immediately after the observation window (the first three months). This suggests that managers can use early knowledge of game sales, such as pre-order sales numbers, to fine-tune their sales forecast while using this method. Overall, the jump-decay model, with substantially lower MAPE, is the best model across all models.

In a nutshell, the within-sample and out-of-sample forecasts show that the jump-decay model gives superior fit within-sample and in time-series out-of-sample forecasts and is comparable to the best alternative model in cross-section, out-of-sample prediction.

Managerial Implications and Conclusions

Prior literature on fast-decay products treats deviations from the exponential lifecycle as trivial noise. Our study is the first attempt to understand sales jumps that can occur in fast-decay product categories. We highlight the importance of including the sales jumps as a key feature of the product lifecycle of fast-decay products. Contrary to the common assumption of a strictly exponential decay function, sales jumps account for a substantial portion of total game sales. We develop a jump-decay model that explicitly models the exponential decline in sales after launch and sales jumps. We compare our model to a number of models drawn from the extant literature and show how our model is more strongly and accurately predictive than the other models. We test our model on data from 2396 games from nine console platforms over the period from January 2004 to November 2011.

We summarize our findings, discuss their implications, and point out some limitations.

Summary of Findings

Based on our analysis of 2396 video games, we find the following:

1. Higher product quality benefits a game through much higher sales at launch, but it does not affect the rate of sales decay.
2. Sequels reward firms in many ways: higher sales at launch, lower rate of sales decay, and larger sales jumps.
3. A larger installed console base or launch during holidays does not affect the sales after controlling for other factors.
4. Price promotions of consoles by competitors negatively affect the occurrence of sales jumps, but less so than the price promotions of other compatible consoles by the same firm.
5. The impact of an upgrade or new launch by a competitor negatively affects the occurrence of sales jumps, but less so than when these announcements are related to the base console or to other compatible consoles from the same manufacturer.

A natural question to ask is what are the implications of simply using the commonly applied exponential modeling framework in the presence of sales jumps? The result is a more parsimonious model but with a slower sales decay rate that treats actual sales as a series of peaks and troughs around predicted values; it is also in conflict with many managers' mental models, possibly limiting its usage. Interestingly, in our data, we find that when using an exponential modeling framework, approximately 18% of total sales are contained in underpredicted spikes and 14% of total sales are in overpredicted troughs.

Impact of Game-Specific Characteristics on Sales

We estimate the impact of each of the game-specific characteristics on the sales of a game. We obtain this by first "creating" a representative game—one that takes on baseline values for game-specific characteristics (e.g., a non-sequel in a common genre played on a Sony console) and that performs like an average game in terms of duration and number of jumps. Using only the significant parameter estimates, we estimate the percentage change in sales by one unit of change in a particular game characteristic. Table 4a presents the results. We find that a ten-point increase in quality rating is associated with a sales increase of 24%. A non-sequel game could gain a 42% increase in sales if designed as part of a franchise. A game with the same characteristics but only a change in platform from Sony to Nintendo would gain 2% sales. Thus our model can help managers make decisions on the design characteristics of a game.

[Insert Table 4]

Policy Simulation

We also conduct a policy simulation experiment to test the impact of change in frequency of new console launch/upgrade announcements on game sales. We create six different scenarios, where each console manufacturer is assumed to either double (or halve) the frequency of its console launch/upgrade announcements in comparison to the current frequency. We achieve this by either inserting a hypothetical announcement between every two existing announcements or removing one announcement out of every two from the current list. Table 4b presents the results. We find that: (1) Microsoft cannot benefit from either experiment. Doubling or halving its announcements will both decrease the game sales on its consoles and benefit games on Nintendo platform consoles. (2) Sony will also cause game sales decay on its own consoles in both experimental scenarios. By doubling its announcements it will inadvertently boost the game sales for both Microsoft and Nintendo consoles. (3) Nintendo games have the most to gain from both experiments. Out of the two scenarios, Nintendo can increase game sales more (9.22%) by doubling its launch/upgrade frequency. In this scenario, games on Microsoft and Sony consoles will both lose sales. To summarize, Microsoft and Sony are already carrying out their optimal launch/upgrade announcement strategies, while Nintendo could increase game sales by 10% if it were to double its launch/upgrade announcements.

Robustness of Results

We carried out the following analyses to assess the robustness of our results. First, though concerns might be raised that the theoretical relatedness in some of our independent variables could create a problem of multicollinearity, we find that the results of the jump-decay model are very robust with regard to the selection of variables. In particular, the significance and effect of each variable do not change much whether the variable is included individually or combined with all others. The correlations among game-specific variables are all less than 0.5. Similarly, the correlations among the time-varying variables, such as game price, console price index, and events dummies, are also less than 0.5. Thus we do not view multicollinearity as a problem.

Second, we tested the model with different metrics for game quality. We collected data on quality, which was measured using three metrics: a percentage score based on user reviews, an overall rank within the focal game's console platform, and an overall rank across all platforms. We could only find data for 1504 games using these metrics. The correlation between these metrics is high ($>.75$; $p \leq .01$). We chose to retain the original metric to report the final results to avoid losing the games where data on quality is not available for all games.

Implications

This study has several implications for managers, software/game developers, and modelers. First, this study is the first to examine the information content in sales spikes. We examine how key variables under managerial control during the new product development phase, namely quality, sequel, or month of launch, may affect key aspects of the sales cycle, especially the sales at launch, the decay rate, and the occurrence of sales spikes. We show that sales of products in fast-decay categories experience sales spikes. The deviations from a naïve model are substantial and thus have serious implications on new product development and sales, including inventory management.

Second, our results caution managers against choosing mainly tactical strategies, such as the month of launch, over serious investments in higher quality and/or the development a franchise of games through multiple sequels. Higher quality games experience higher sales at launch, but the benefits do not appear to affect the rate of decay. On the other hand, sequels, which require a higher investment, experience not only higher sales at launch but also have a slower rate of decay and larger sales spikes. Thus the efforts to improve quality or investments in building strong franchises need to be managed well against the costs of pursuing such initiatives. In contrast, changing the month of launch to the holiday period without any change in game characteristics is unlikely to yield any increase in sales.

Third, managers need to consider the negative cannibalization effects of new announcements on sales spikes of existing games. When firms make an announcement regarding the launch of new consoles or upgrades/price cuts of existing products, the announcement suppresses sales spikes in older games. Our model suggests that both types of announcements have a greater negative effect when they are related to consoles by the same firm rather than to consoles by competitor firms. These findings underscore the significant impact of customer lock-in in these markets.

Finally, our study has a number of limitations, many of which have implications for data collection and could serve as the basis of future research. First, our study is limited to a single category of fast-decay products. Although sales spikes occur in other categories as well, generalization requires the extension of research to other categories. We limit our analyses to one category because of the availability of data and the prevalent nature of pre-announcement strategies in the video games industry. Second, we do not distinguish between pre-announcements and vaporware. Vaporware is the practice of announcing a product far in advance of its availability and implies deception on the part of the firm. Future research is required to distinguish between the effects of these two types of pre-announcements. Third, we include only official pre-announcements made by firms and do not include publicly available rumors regarding the date of event. Such information can nonetheless affect customer buying behavior and hence both sales decay and sales spikes. Another potential limitation is lack of control for competition. We include competitors' events and seasonality to control for competition (seasonality works because many more games enter or make price cuts following seasonal patterns). However, we do not control for the exact game price movement or advertising spending by a particular competitor.

References

Ainslie, Andrew, Xavier Drèze, and Fred Zufryden (2005), "Modeling Movie Lifecycles and Market Share," *Marketing Science* 24(3), 508-17.

Bass Frank M., Dipak Jain, and Trichy V. Krishnan (2000), "Modeling the Marketing-Mix Influence in New Product Diffusion," in *New-Product Diffusion Models*, Vijay Mahajan, Eitan Muller, and Yoram Wind, ed. Boston, MA: Kluwer Academic, 99-124.

Bass, Frank M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science* 15(1), 215-27.

Bass, Frank M., Trichy V. Krishnan and Dipak C. Jain (1994), "Why the Bass Model Fits without Decision Variables," *Marketing Science* 13(3), 203-23.

Binken, Jeroen L.G. and Stefan Stremersch (2009), "The Effect of Superstar Software on Hardware Sales in System Markets," *Journal of Marketing* 73(2), 88-104.

Chintagunta, Pradeep K., Harikesh S. Nair, and R. Sukumar (2009), "Measuring Marketing-Mix Effects in the 32/64 Bit Video-Game Console Market," *Journal of Applied Economics* 24, 421-45.

Clements, Matthew T. and Hiroshi Ohashi (2005), "Indirect Network Effects and the Product Life Cycle: Video Games in the U.S., 1994-2002," *The Journal of Industrial Economics* 53(4), 515-42.

Corts, Kenneth S. and Mara. Lederman, "Software Exclusivity and the Scope of Indirect Network Effects in the US Video Game Market," *International Journal of Industrial Organization*, 27, 121-136.

Gretz, Richard T. (2010), "Hardware Quality vs. Network Size in the Home Video Game Industry," *Journal of Economic Behavior & Organization*, 76(2), 168-83.

Hernandez-Mireles, Carlos, Dennis Fok, Philip Hans Franses (2011), "The Triggers, Timing and Speed of New Product Price Landings," Working Paper, Erasmus University, Rotterdam.

Katz, Michael and Carl Shapiro (1985), "Network Externalities, Competition, and Compatibility," *American Economic Review*, 75(3), 424-40.

Katz, Michael and Carl Shapiro (1986), "Technology Adoption in the Presence of Network Externalities," *Journal of the Political Economy*, 94, 822-41.

Lehmann, Donald R. and Charles B. Weinberg (2000), "Sales through Sequential Distribution Channels: An Application to Movies and Videos," *Journal of Marketing*, 64(3), 18-33.

Luan, Y. Jackie and K. Sudhir (2010), "Forecasting Marketing-Mix Responsiveness for New Products," *Journal of Marketing Research*, 47(3), 444-57.

Moe, Wendy W. and Peter S. Fader (2001), "Modeling Hedonic Portfolio Products: A Joint Segmentation Analysis of Music Disc Sales," *Journal of Marketing Research*, 28(3), 376-85.

Nair, Harikesh (2007), "Intertemporal Price Discrimination with Forward-Looking Consumers: Application to the U.S. Market for Console Video-Games," *Quantitative Marketing and Economics*, 5(3): 239-92.

Radas, Sonja and Steven M. Shugan (1998), "Seasonal Marketing and Timing New Product Introductions," *Journal of Marketing Research*, 35(3), 296-315.

Rossi, Peter E., Greg M. Allenby, and Robert McCulloch (2005), *Bayesian Statistics and Marketing*, West Sussex, England: John Wiley & Sons.

Sawhney, Mohanbir S. and Jehoshua Eliashberg (1996), "A Parsimonious Model for Forecasting Box-Office Revenues of Motion Pictures," *Marketing Science*, 15(2), 113-31.

Schilling, Melissa A. (2003), "Technological Leapfrogging: Lessons from the U.S. Video Game Console Industry," *California Management Review*, 45(3): 6-32.

Srinivasan, A. and N. Venkataraman (2010), "Indirect Network Effects and Platform Dominance in the Video Game Industry: A Network Perspective," *IEEE Transactions on Engineering Management*, 57(4), 661-73.

Srinivasan, V. and Charlotte H. Mason (1986), "Nonlinear Least Squares Estimation of New Product Diffusion Models," *Marketing Science*, 5(2), 169-78.

Table 1
COMPARISON OF MODELS

Models	**Includes Time-Varying Variables**	**Accounts for Seasonality**	**Allows Out-of-Sample Forecasts**	**Explains Drivers of Sales Jumps**
Exponential Model (XM)	No	No	Yes	No
Generalized Gamma Model (GGM)	No	No	Yes	No
Generalized Bass Model (GBM)	Yes	Yes	Yes	No
Semiparametric Proportional Hazard Model (SPPH)	Yes	Yes	No	No
Jump-Decay Model (JDM)	Yes	Yes	Yes	Yes

Table 2: ESTIMATION RESULTS (Equation 6)

EXPONENTIAL DECAY SUB-MODEL

Variables	Sales At Launch		Decay Rate	
	Est	p-val	Est	p-val
Constant	**6.80**	.00	**-.12**	.00
Quality	**.02**	.00	-.0001	.24
Sequel	**.37**	.00	**-.01**	.00
Holiday Launch	.07	.10	.00	.71
Installed Base	-.02	.57	.00	.59
Nintendo	.04	.34	**-.01**	.00
Microsoft	**-.11**	.05	.00	1.00
Sports	.09	.19	**-.04**	.00
Adventure	**.16**	.02	-.01	.22
Action	**.22**	.00	.00	.37
Music	.11	.18	-.01	.06
Simulation	**.24**	.00	-.01	.30
Puzzles	**.47**	.00	-.01	.53
Fitness	**1.30**	.00	-.03	.12
2009 Dummy	**.27**	.00	**-.01**	.04
2010 Dummy	**.50**	.00	.00	.70

V(1,1)	**.86**	.00
V(1,2)	**-.02**	.00
V(2,2)	**.005**	.00
Jump size variance	**.02**	.00
Model error variance	**.03**	.00

SALES JUMP SUB-MODEL

Variables	Jump Size		Jump Probability	
	Est	p-val	Est	p-val
Constant	**.45**	.00	**1.60**	0.00
Quality	**-.001**	.00		
Sequel	**.02**	.01		
Holiday Launch	-.01	.42		
Installed Base	.01	.21		
Nintendo	**.03**	.00		
Microsoft	**-.03**	.00		
2009 Dummy	**-.06**	.00		
2010 Dummy	**-.07**	.00		
Console Price Index			**.01**	.00
Game Price (Log)			**-.08**	.00
Launch/Upgrade of Base Console			**-.10**	.00
Launch of Competitor Console			**-.06**	.00
Launch of Compatible Console			**-.10**	.00
Price Cut of Competitor Console			**-.02**	.00
Price Cut of Compatible Console			**-.06**	.00
Feb			**-.01**	.00
Mar			.00	.45
Apr			**-.26**	.00
May			**-.29**	.00
Jun			**-.02**	.00
Jul			**-.16**	.00
Aug			**-.19**	.00
Sep			**-.15**	.00
Oct			**-.29**	.00
Nov			**.09**	.00
Dec			**.46**	.00

Table 3
COMPARISON OF PREDICTIVE ACCURACY

Model Name	Within-Sample		Cross-Section		Time-Series	
	Mean	Median	Mean	Median	Mean	Median
N	77600		79055		69706	
Exponential	1.40	.83	1.60	.88	1.00	.99
Generalized Gamma	.75	.90	1.09	.80	1.53	.95
Generalized Bass	.75	.95	.82	.98	.87	1.00
Semiparametric Proportional Hazard	.60	.45	NA			
Jump-Decay Model	.50	.43	1.04	.74	.78	.91
BEST MODEL	Jump-Decay	Jump-Decay	Generalized Bass	Jump-Decay	Jump-Decay	Jump-Decay

Table 4
POLICT SIMULATION

Table 4a: Impact of change in strategy variable on sales

Variable	% Change in Sales	Remarks
Quality	24%	10-point increase in quality
Sequel	42%	From non-sequel to sequel
Launch Month in Holidays	0%	From holiday to nonholiday
Installed Hardware Base	0%	1% change in installed base
Nintendo	2%	Change of label from Sony to Nintendo or Microsoft
Microsoft	-20%	
Genre: Sports	-26%	Change of genre from “Others” category, which comprised the "driving," "strategy," and "simulation" genres, to game-specific genres.
Genre: Adventure+Platformer	17%	
Genre: Shooter+Action+Fighting	25%	
Genre: Party+Music	0%	
Genre: Life Simulator+Role Play	27%	
Genre: Puzzle Brain	60%	
Genre: Fitness	267%	

Table 4b: Percentage of Sales Changes in Launch/Upgrade Event Policy Simulation

Strategy		Console Manufacturer		
		Microsoft	Sony	Nintendo
Half	**Microsoft**	-1.63%	-4.63%	2.53%
	Sony	-1.94%	-3.94%	.01%
	Nintendo	-.13%	-3.30%	2.51%
Double	**Microsoft**	-5.21%	-4.69%	1.39%
	Sony	6.23%	-1.36%	2.35%
	Nintendo	-3.29%	-5.27%	9.22%

Figure 1
SAMPLE OF UNITS SALES FOR FAST-DECAY PRODUCTS OVER TIME FROM PRIOR STUDIES

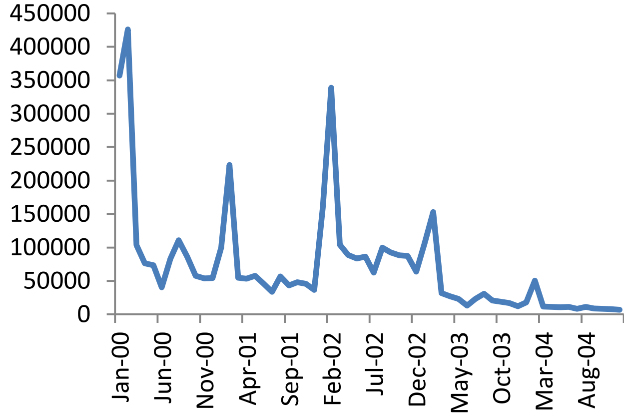

Figure 1a: Sales of Halo (Xbox)

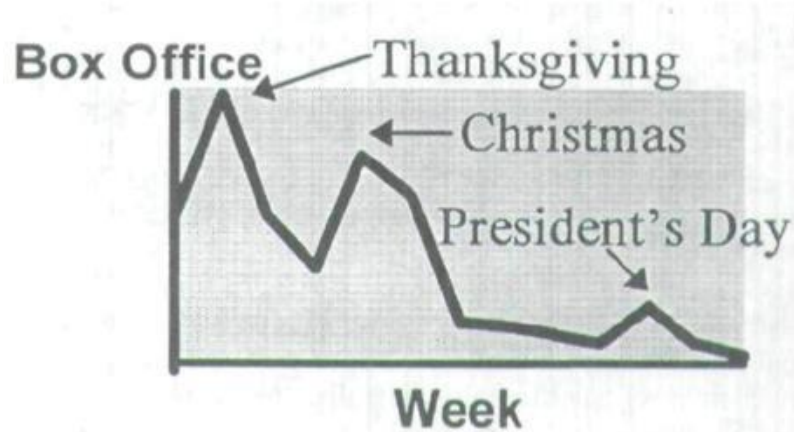

Figure 1b: Movie (Radas and Shugan 1998, Fig.6)

Figure 1c: Music CD (Moe and Fader 2001, Fig.1)

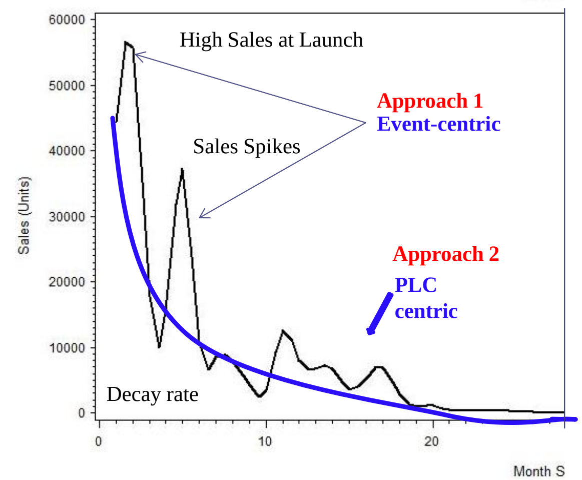

Figure 1d: Common Approaches to Modeling Sales

Figure 2
CONCEPTUAL FRAMEWORK

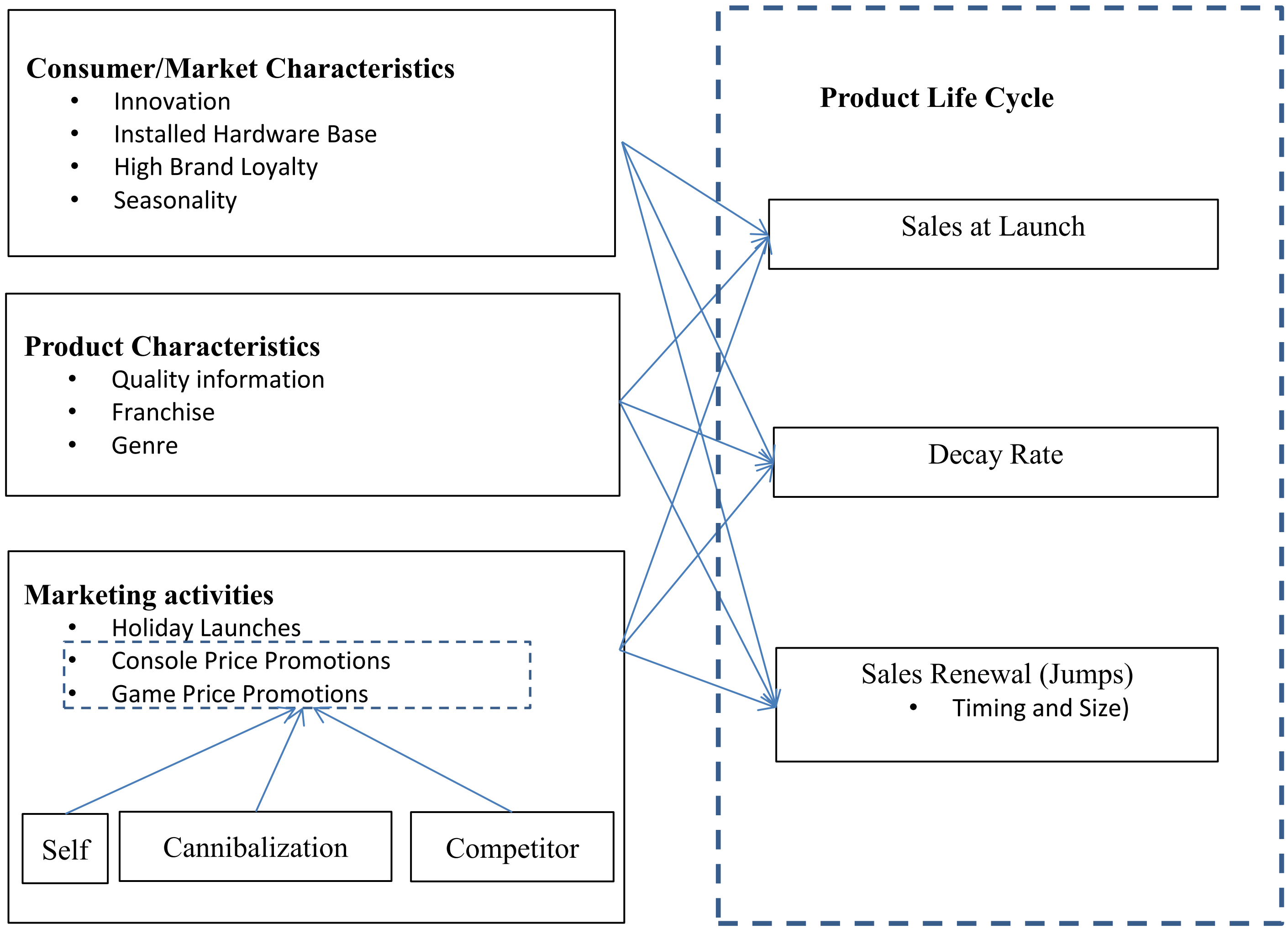

Figure 3
FITTED VERSUS ACTUAL SALES: MODEL COMPARIONS

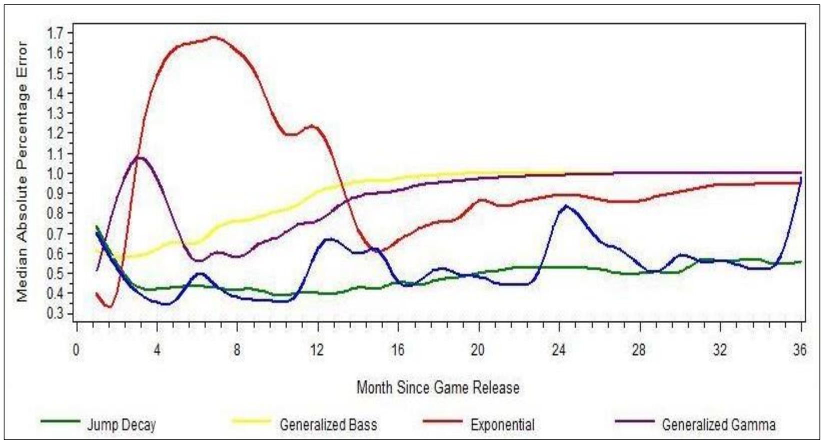

Figure 3a Median APE Model Comparison on Within-Sample Fit

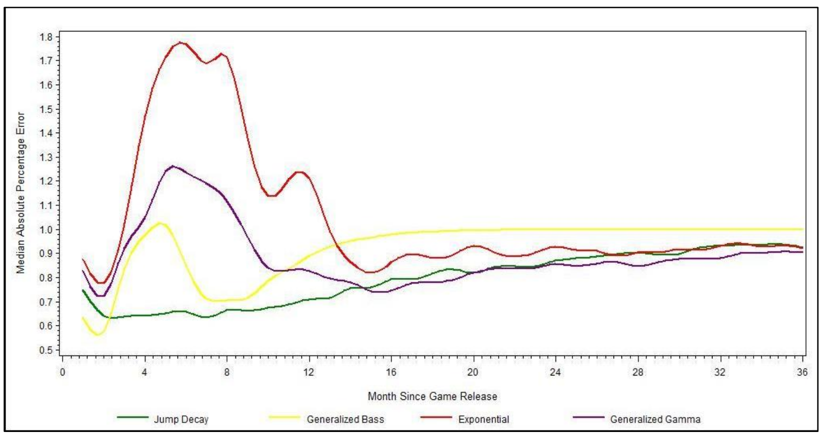

Figure 3b Median APE Model Comparison on Cross-Section Out-of-Sample Forecast

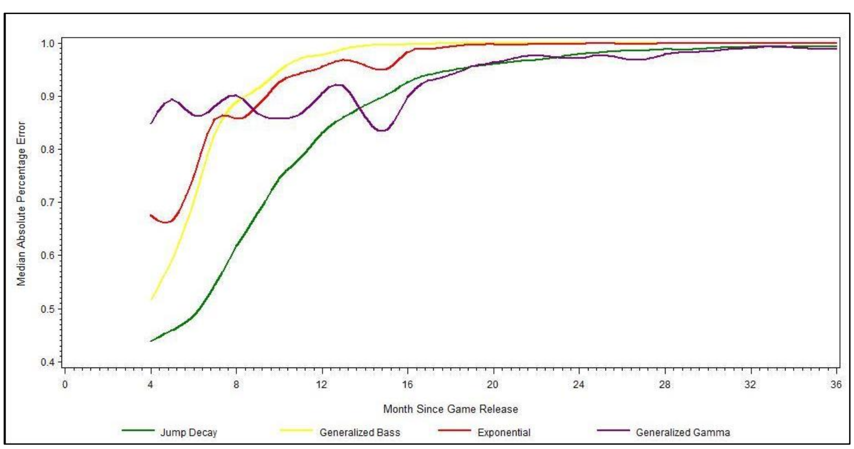

Figure 3c Median APE Model Comparison on Time-Series Out-of-Sample Forecast

Appendix A: Bayesian Estimation of the Model

In this appendix, we lay out the prior and posterior distribution of our model, as well as the estimation details necessary for the estimation of the model.

Model

$$y_{j,t} \equiv ln(S_{j,t}) = X_{j,t}'\beta_j + k_j J_{j,t} + \sigma\varepsilon_{j,t}$$

$\varepsilon_{j,t} \sim N(0,1), J_{j,t} \sim Poisson(exp(Z_{j,t}'\gamma))$

$k_j = W_j{}'\Delta + u_j,\ u_j \sim N(0, \sigma_k^2)$

$\beta_j = V_j'\bar{\beta} + v_j,\ v_j \sim N(0, \Sigma_\beta)$

j=1,..., N. t=1,...,T. N is the number of games, and T is the total number of time periods. X, Z, W are exogenous variables. $K \equiv (k_1, k_2, \dots, k_N)$.

Parameters: $\boldsymbol{\theta} = (\bar{\boldsymbol{\beta}}, \boldsymbol{\Sigma_\beta}, \boldsymbol{\sigma^2}, \Delta, \boldsymbol{\sigma_k}^2, \boldsymbol{\gamma}')$,

Priors: $\bar{\boldsymbol{\beta}}|\boldsymbol{\Sigma_\beta} \sim \boldsymbol{N}(\bar{\bar{\boldsymbol{\beta}}}, \boldsymbol{\Sigma_\beta} \otimes \boldsymbol{A_\beta^{-1}})$

$$\Sigma_\beta \sim IW(v_0, V_0)$$

$$\sigma^2 \sim IG(a_\sigma, b_\sigma)$$

$$\Delta|\sigma_k^2 \sim N(\bar{\Delta}, \sigma_k^2 A_k^{-1})$$

$$\sigma_k^2 \sim IG(a_k, b_k),$$

$$\gamma \sim N(\bar{\gamma}, A_\gamma^{-1})$$

Posterior Distributions:

1. β $\quad \beta_j|y_j, X_j, J_j, k_j, \Sigma_\beta, \sigma^2 \sim N(\tilde{\beta}_j, \left(\frac{X_j{}'X_j}{\sigma^2} + \Sigma_\beta{}^{-1}\right)^{-1})$

$$\tilde{\beta}_j = \left(\frac{X_j{}'X_j}{\sigma^2} + \Sigma_\beta{}^{-1}\right)^{-1}\left(\frac{X_j{}'(y_j - k_j J_j)}{\sigma^2} + \Sigma_\beta{}^{-1} * (V_j'\bar{\beta})\right)$$

(1.2) $p(\bar{\beta}, \Sigma_\beta|\beta_1, \dots, \beta_N, A_\beta, v_0, V_0)$, denote $(\beta_1, \dots, \beta_N) = \vec{\beta}$

$$\bar{\beta}|\vec{\beta}, A_\beta, \Sigma_\beta \sim N\left(\left(V'V + A_\beta^{-1}\right)^{-1}\left(V'\tilde{\beta} + A_\beta^{-1}\bar{\bar{\beta}}\right), \Sigma_\beta \otimes A_\beta^{-1}\right)$$

$$\Sigma_\beta|\vec{\beta}, A_\beta, \bar{\beta} \sim IW(v_\beta, V_\beta)$$

$$v_\beta = v_0 + N, V_\beta = V_0 + S$$

$$S = \left(\vec{\beta} - I_n\bar{\beta}\right)'\left(\vec{\beta} - I_n\bar{\beta}\right) + \left(\bar{\beta} - \bar{\bar{\beta}}\right)' A_\beta \left(\bar{\beta} - \bar{\bar{\beta}}\right)$$

2. σ^2

$$\sigma^2 \,|y, X, J, K, \vec{\beta} \sim IG(\widehat{a_\sigma}, \widehat{b_\sigma})$$

$$\widehat{a_\sigma} = a_\sigma + N * T/2, \widehat{b_\sigma} = 2b_\sigma + (N * T)\widehat{s_\sigma^2}$$

$$(N * T)\widehat{s_\sigma^2} = \left(y - X'\vec{\beta} - K'J\right)'\left(y - X'\vec{\beta} - K'J\right)$$

3. J_t

$$p\left(J_{j,t} = n \middle| y_{j,t}, X_{j,t}, Z_{j,t}, k_j, \beta, \gamma, \sigma^2\right) \propto \frac{\exp\left(Z_{j,t}'\gamma\right)^{\mathrm{n}}}{n!} \exp\left[-\exp\left(Z_{j,t}'\gamma\right)\right] * \exp\left[-\frac{1}{2\sigma^2}\left(y_{j,t} - X_{j,t}\beta_j - k_j n\right)^2\right],$$

n=0,1,2,...,10 (theoretically n=0,1,...,∞, however empirically 10 is sufficient)

4. K, use $\tau = (\Delta, \sigma_k^2)$, $h = (\bar{\Delta}, \mathrm{A_k})$

$$p\left(K, \tau \middle| y, X, Z, W, J, \vec{\beta}, \gamma, \sigma^2\right) \propto \left[\prod_j p\left(y_j|\theta_j\right)p(\theta_j\,|\,\tau)\right] \times p(\tau|h)$$

We follow the hierarchical models estimation procedure in Rossi, Allenby and McCulloch (2005) and draw the posterior k_j and τ in two steps.

(3.1) $$p\left(k_j\middle|\tau, y_j\right), \tau = (\Delta, \sigma_k^2),$$

$$p\left(k_j\middle|\tau, y_j, X_j, J_j, W_j, \beta_j, \sigma^2\right) \propto p\left(y_j\middle|k_j, X_j, J_j, W_j, \beta_j, \sigma^2\right)p\left(k_j\middle|\tau\right)$$

$$k_j|\tau, y_j \sim N\left(\widetilde{k_j}, \left(\frac{J_j'J_j}{\sigma^2} + \frac{1}{\sigma_k^2}\right)^{-1}\right);\quad \widetilde{k_j} = \left(\frac{J_j'J_j}{\sigma^2} + \frac{1}{\sigma_k^2}\right)^{-1}\left(\frac{J_i'(y_j - X_j'\beta_j)}{\sigma^2} + \frac{W_j{}'\Delta}{\sigma_k^2}\right)$$

(3.2) $$p(\tau|K, W, h), h = (\bar{\Delta}, \mathrm{A_k})$$

Since $K = (k_1, k_2, \ldots, k_N), K = W'\Delta + U,\ U \sim N(0, \sigma_k^2 I)$

$$\Delta|\mathrm{K}, \mathrm{W}, \mathrm{h} \sim N\left(\widetilde{\Delta}, \sigma_k^2 A_k^{-1}\right)$$

$$\widetilde{\Delta} = (W'W + A_k^{-1})^{-1}(W'K + A_k^{-1} \cdot \overline{\Delta})$$

$$\sigma_k^2 | K, h \sim IG(\widehat{\alpha_k}, \widehat{\beta_k})$$

$$\widehat{\alpha_k} = \alpha_k + N/2,\ \ \widehat{\beta_k} = \frac{2\beta_k + N\widehat{s_k}^2}{2\widehat{\alpha_k}}$$

$$N\widehat{s_k}^2 = \left(\Delta - W'\widehat{\Delta}\right)'\left(\Delta - W'\widehat{\Delta}\right) + \left(\widetilde{\Delta} - \overline{\Delta}\right)' A_k \left(\widetilde{\Delta} - \overline{\Delta}\right)$$

5. γ

$$f(\gamma) = p(\gamma|J, Z) \propto \prod_{j=1}^{N}\prod_{t=1}^{T} \frac{(\mathrm{e}^{Z'_{j,t}\gamma})^{\mathrm{J_{j,t}}}}{J_{j,t}!} \exp\left[-\exp\left(Z'_{j,t}\gamma\right)\right] * \frac{1}{\sqrt{2\pi\sigma_\gamma^2}} exp\left[-\frac{1}{2\sigma_\gamma^2}(\gamma - \mu_\gamma)^2\right]$$

The posterior of γ does not follow any well know distribution, therefore we can't draw directly. We use random walk Metropolis-Hasting algorithm to make the posterior draws.

In the implementation, we calculate the log form of the posterior and then convert it back with exponential transformation.

$$\log\left(f(\gamma)\right) \propto \sum_{j=1}^{N}\sum_{t=1}^{T}[-\exp(Z'_{j,t}\gamma) + J_{j,t}(Z'_{j,t}\gamma) - \log(J_{j,t}!)] - \frac{1}{2\sigma_\gamma^2}(\gamma - \mu_\gamma)^2$$

For the random walk Metropolis-Hasting algorithm, we specify the transition function as:

$$\gamma' = \gamma + \epsilon, \epsilon \sim N(0, s^2\Sigma)$$

s is the scaling factor to improve the efficiency of the M-H process. It usually take the value of $2.3/\sqrt{d}$. (*d* is the dimension of γ). Σ is the transition matrix, which can be taken as identity matrix or variance-covariance matrix of the parameter estimates from MLE. In each iteration, we compute $\alpha = min\left\{1, \frac{f(\gamma')}{f(\gamma)}\right\}$. With probability α, the new γ takes the value of γ', otherwise the new γ takes the value of old γ.

Appendix B: Details on Cross Section and Time Series Out of Sample Forecast

This appendix explains how we conduct the cross section and time series out of sample forecast for Jump Decay model as well as various comparison models.

Within Sample Fit

After obtaining the parameter estimates from each model, we combine them with the independent variables to generate the within sample prediction on game sales. For each model $Sales_{gt}$=f($X_{g,t}$, β ,error),we use the estimated parameters ($\hat{\beta}$) and the independent variables ($X_{g,t}$) to calculate the expected value of sales E($Sales_{gt}$)=f($X_{g,t}$, $\hat{\beta}$). That gives us the within sample prediction of each model.

Cross-Sectional Forecast

Since all alternative model parameters are game-specific, we cannot use them directly for out-of-sample forecast. Therefore, we follow the treatment of Sawhney and Eliashberg (1996) in developing cross-section forecasts:

1. We use ten-fold cross-validation by randomly partitioning the entire games sample into ten equal groups. We hold out one group, estimate each of the models on the remaining nine groups and then form predictions on the held out group. We repeat this process ten times, for each of the ten held-out groups of data.
2. Regress general parameters θ_j (such as m_j and λ_j in Exponential Model, λ_j, γ_j and N_j in Generalized Gamma Model and $p_j, q_j, m_j and\ \beta_j$ in Generalized Bass Model) onto game-specific characteristics V_j (e.g., genre). These game-specific characteristics are the same across models and are explained in the decay sub model section.

3. Combine OLS parameter estimates $\vec{\kappa} = \left(V_j'V_j\right)^{-1}(V_j'\theta_j)$ with game characteristics in the forecast sample V_i to forecast the out-of-sample game-specific parameters $\widehat{\theta_i} = V_i'\vec{\kappa}$.
4. Check if the forecasted parameters $\widehat{\theta_i}$ is out of reasonable scope (e.g., $\widehat{m_j}$ <0, $\widehat{\lambda_j} < 0$ in exponential model, $\widehat{p_j} + \widehat{q_j} < 0$ or $\frac{\widehat{q_j}}{\widehat{p_j}} < 0$ in generalized Bass Model), and will lead to a negative or zero sales forecast. If yes, replace the forecasted parameter value with the average value of that parameter from the estimation sample.
5. For the Generalized Bass Model, we calculate the median value for the monthly dummies $\overline{\gamma_l}, (l = 1, \ldots, 12)$ for each month, as well as the median value for console events dummies $\bar{\lambda}_k$ $(k = 1, \ldots, 5)$, and used them as forecasted parameters in the forecast samples.

Time-Series Forecast

We follow the same steps as above for developing time-series forecasts with one key difference. For the time-series forecasts, we estimate each of the models using data from months 1 to 3 and then form predictions on the held out group for months 4 to 36. This procedure is consistent with Sawhney and Eliashberg (2001) who suggest incorporating the first few months of sales into the estimation to improve the forecast accuracy of the remaining periods. We use as few months as possible for calibration in part because the average game sales drops quickly over time, and thus so is the economic value of the forecast. Hence, we use the first 3 months of sales of each game to calibrate the models and forecast the remaining months. We did not re-estimate the parameters within $\mathrm{X_j(t)}$ in Generalized Bass Model, since their numbers exceed the number of observations (3 for each game) and cannot be identified. Instead we used cross-section parameter predictions for these parameters.

In addition to the parameter checks in cross section forecast, we check the newly estimated parameters to make sure they are within reasonable scope, if not, they are replaced with the initial values (which was generated from the OLS parameters based on estimation sample estimates). In our model, when the time series forecast of "decay" parameter is positive, we replace it with the sample average decay , and replace the "initial sales" parameter with the real sales of period 3 minus the fitted jumps. For the remaining games (where the 'decay' parameter is negative), we took the mean of the estimated game level decay rate and average decay rate. This adjustment is due to the fact that game sales decay faster in early periods.