The Triggers, Timing and Speed of New Product Price Landings

Carlos Hernandez-Mireles, Dennis Fok and Philip Hans Franses

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Email address corresponding author	mireles@ese.eur.nl
Address	Erasmus Research Institute of Management (ERIM) RSM Erasmus University / Erasmus School of Economics Erasmus Universiteit Rotterdam P.O.Box 1738 3000 DR Rotterdam, The Netherlands Phone: + 31 10 408 1182 Fax: + 31 10 408 9640 Email: info@erim.eur.nl Internet: www.erim.eur.nl

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ABSTRACT AND KEYWORDS	
Abstract	Many high-tech products and durable goods exhibit exactly one significant price cut some time after their launch. We call this sudden transition from high to low prices the price landing. In this paper we present a new model that describes two important features of price landings: their timing and their speed. Prior literature suggests that prices might be driven by sales, product line pricing, competitor's sales or simply by time. We propose a model using mixture components that identifies which of these explanations is the most likely trigger of price landings. We define triggers as thresholds after which prices are significantly cut. In addition, price landings might differ across products and therefore we model their heterogeneity with a hierarchical structure that depends mainly on firm, product type and seasonal effects. We estimate our model parameters applying Bayesian methodology and we use a rich dataset containing the sales and prices of 1195 newly released video-games (VG's). In contrast with previous literature, we find that competition and time itself are the main triggers of price landings while past sales and product line are less likely triggers. Moreover, we find substantial heterogeneity in the timing and speed of price landing across firms and product types.
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The Triggers, Timing and Speed of New Product Price Landings

Carlos Hernandez-Mireles, Dennis Fok, Philip Hans Franses
Erasmus Research Institute of Management
Erasmus University Rotterdam

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Abstract

Many high-tech products and durable goods exhibit exactly one significant price cut some time after their launch. We call this sudden transition from high to low prices the *price landing*. In this paper we present a new model that describes two important features of price landings: their timing and their speed.

Prior literature suggests that prices might be driven by sales, product line pricing, competitor's sales or simply by time. We propose a model using mixture components that identifies which of these explanations is the most likely *trigger* of price landings. We define *triggers* as thresholds after which prices are significantly cut. In addition, price landings might differ across products and therefore we model their heterogeneity with a hierarchical structure that depends mainly on firm, product type and seasonal effects.

We estimate our model parameters applying Bayesian methodology and we use a rich dataset containing the sales and prices of 1195 newly released video-games (VG's). In contrast with previous literature, we find that competition and time itself are the main triggers of price landings while past sales and product line are less likely triggers. Moreover, we find substantial heterogeneity in the timing and speed of price landing across firms and product types.

KEYWORDS: PRICING, PRICING MODELS, NEW PRODUCTS

1 Introduction

"*Don't get us wrong – price cuts are a good thing*"

Wired.com (2007)

It is well known that prices of new products exhibit one or several important price cuts during their life-cycle. Nowadays, we are witnessing how many new high-technology products are introduced at an initial high price and after a certain moment their prices are cut to a permanent and much lower level. This practice is commonly followed by manufacturers of products like video-games, apparel, PCs, movies, and so on. Moreover, scholars have recognized and studied this type of pricing strategy. For example, studies like Feng and Gallego (1995) and Gupta et al. (2006) point that managers at apparel retailers in New York City report the timing and depth of price cuts are important decision variables and the depth of the price cut in this industry is typically between 25 and 50%. In this article, we will call this sudden transition from an initially high price to a lower price level the *price landing*.

We are not aware of any empirical study of price landings. This is quite a surprise because the timing of a permanent price cut for a new product is without a doubt an important managerial decision. During the first half of 2007 thousands of American customers purchased Apple's iPhone and they witnessed a $200 price drop just 66 days after its release. Consumers were outraged by the sudden price drop and Apple apologized and issued a $100 store credit to everyone who purchased the iPhone before April 2007. More recently, the forthcoming market launch of Apple's iPad has brought attention to the pricing strategy that the Apple Store will apply to e-books. According to journalists, Apple is pushing the industry to apply "variable pricing which apparently is *triggered* by sales volume and not just pricing whim", see Wired Magazine (2010). In some instances Apple's timing of price cuts have been judged too early if they happened short time before the Christmas season and in other instances the price cuts have been judged as occurring too late to stimulate further sales or to fight competition. See BusinessWeek

Online (2007) and BusinessWeek Online (2008) for more details on Apple's story.

In this article we present a new model for *price landings* and the estimation approach we present is particularly useful to describe the moment and speed at which the *price landing* occurs and to simultaneously find the *triggers* of these sudden price transitions. Our work offers a complement to studies like those of Tellis et al. (2003) and Golder and Tellis (1997) because we characterize and describe pricing patters of new products while these latter authors have studied and characterized new products' sales patterns. On the other hand, our modeling approach goes further than a description of price patterns because it allows us to find what are the most likely *triggers* of price landings. We apply our model to the market of video-games and to a rich data set that concerns 1195 newly released video-games.

The plan of the article is as follows. In Section 2 we present our literature review. In Section 3 we present our data and market context. Next in Section 4 we present our modeling approach and in Section 5 we present our results. We present our conclusions in Section 6. All figures and tables are presented in Section 7. We present the estimation approach in Appendix A.

2 Literature Review

In this section we review the studies concerned with the video-game industry in subsection 2.1 and next in subsection 2.2 we review the literature related to new products pricing.

2.1 Research on Video-Games

Three empirical studies closely related to our work are Clements and Ohashi (2005), Nair (2007) and Chintagunta et al. (2009).

Clements and Ohashi (2005) study the indirect network effects between video-game consoles and video-games and the effects of consoles' prices on their own sales. Their findings suggest that price elasticity is low at the beginning and high at the end of the life cycle of video-game consoles. Chintagunta et al. (2009) investigate the effects of software availability and prices on the sales of video-game consoles. They propose an econometric approach that accounts for the endogeneity of price and sales and they find time varying price elasticities. In contrast with Clements and Ohashi (2005), Chintagunta et al. (2009) find some evidence of both declining and increasing elasticities. Other studies, like Parker (1992) and Simon (1979), report that elasticities may show diverse time profiles across products, like U or inverted U shapes. See Parker (1992, Table 4, page 365).

Nair (2007) studies the video-game software market and he proposes a model that takes into account the interaction between publishers of video-games and two consumer segments formed by high and low valuation gamers. His findings suggest that the optimal pricing by publishers should exhibit declining prices. The price cut rate (that is the slope of the price function) in Nair (2007) depends on the relative size of each of the consumer segments while the overall and initial level of the optimal price depends on the utility discounting factor and the interaction of consumers and firms.

Our study differs markedly from Clements and Ohashi (2005), Nair (2007) and Chintagunta et al. (2009) because our objective is to introduce a model that is flexible enough to capture many different and detailed theoretical features of prices that have been documented in the literature or observed empirically. In this respect, our price model is a generalization based on previous research. In addition, we offer the first empirical study that focuses on price landings and their triggers, timing and speed.

Finally, the methods of Clements and Ohashi (2005), Chintagunta et al. (2009) and Nair (2007) are considered structural while our model may be classified as a reduced form model. A main advantage of our reduced form is that we do not need assumptions regarding supply and demand side interactions or consumer behavior. A disadvantage of our approach is that we can not draw inferences regarding consumer behavior or consumer-firm interactions and that we need assumptions on the form of the price equation. However, the assumptions we will use for the price equation are more flexible than the assumptions of Nair (2007) and Chintagunta et al. (2009). Nair assumes that consumers form expectations based on an auto-regressive process of order one while Chintagunta and colleagues assume that prices are stationary. In contrast, we present a very flexible equation that can capture sudden breaks (non-stationarity) and it allows us investigate what is *triggering* these breaks. Hence, we offer novel findings and we are the first to measure quantitatively empirical features of prices that have not been documented before in the literature. In addition, our econometric approach is computationally simple. Therefore, we can use our method to study relatively large databases of prices. This may be a technical advantage over structural models that are usually much more computationally demanding.

2.2 Research on New Products Pricing

The literature dealing with pricing strategy is extensive and in this section we focus our attention to a set of empirical and analytical studies concerned mainly with new product prices. We present the studies we surveyed in Table 1.

In Table 1, we see that 24 out of 32 studies are analytical while 8 are empirical. Out of these eight empirical studies only Clements and Ohashi (2005), Chintagunta et al. (2009) and Nair (2007) were published recently and only the study of Nair (2007) is focused on pricing policies for new products. To our knowledge, Nair (2007) and our work are the only empirical studies concerned with price patterns. A likely reason of such lack of empirical studies on prices is the scarcity of detailed price data.

We draw the following generalizations the literature in Table 1: 1. Prices show gradual or sudden transition from high to low states. Both empirical and theoretical studies have documented such transitions. 2. Prices show transitions that rarely mimic the S-shape of sales or that increase over time (8 studies). 3. Prices respond to competition, changes in consumer valuations across time, consumer heterogeneity, new product releases, learning curves on costs and market saturation.

The first generalization tell us that prices of new products rarely stay constant. We note that some studies, like Schmalen (1982), Ferguson and Koenigsberg (2007) and

Eliashberg and Jeuland (1986), have shown when it is optimal to keep prices of new products constant. On the other hand, we could hardly draw a consensus about how fast price transitions should be or how they look empirically. Some studies explicitly report the optimal price decrease rate, like in Dockner and Gaunersdorfer (1996), Raman and Chatterjee (1995) and Bayus (1994) while many other studies give less attention specifically to the speed of price transitions. Much more is known about the shape of price transitions. Many studies, like Robinson and Lakhani (1975), Kalish (1983), Dolan and Jeuland (1981), Bayus (1992), show that the optimal policy is for prices to decline over time. Other studies show the optimal mark-down (or optimal sudden price discount) based on the length of the season, the perishability of the product or drastic seasonal changes in consumer valuations or demand. See for example Ferguson and Koenigsberg (2007), Gupta et al. (2006), Rajan et al. (1992) and Feng and Gallego (1995). Finally, diffusion studies, like Rao and Bass (1985), confirm that the declining pattern is an empirical regularity and recent studies, following Bass et al. (1994), usually incorporate the declining price effect on diffusion.

The literature suggests the generalization that prices should change (in most cases drop) once an event modifies the market and that these price drops occur in synchrony with the movements of price drivers. These events are usually related to the drivers listed in the last column of Table 1. In general terms, previous *empirical* literature suggests that x *drives* y when x is an important underlying variable causing the variance in y. In contrast, many *analytical* studies integrate *trigger* variables into their models where x is defined as a *trigger* of y if it has an effect on y only after a certain threshold, for example after $x > x_o$ becomes true where $x > x_o$ might mean, for example, competitive entry, the end of a season or the limit of market potential. For example, Feng and Gallego (1995) and Gupta et al. (2006) incorporate thresholds after which prices should be marked down. We believe there is a disconnect between analytical studies that allow non-linearities and sudden price breaks and empirical studies that assume in most cases linear price functions without structural breaks.

The objective of this article is to fill the literature gaps between empirical and analytical studies of new products' prices. First, our model, together with the econometric approach we use, will allow us describe the theoretical features of prices based on a large database of prices. We focus specifically on the speed and timing of sudden price transitions, what we call *price landings*. Second, we test the relative importance of different price triggers suggested by theoretical and empirical studies simultaneously. We test whether saturation, market entry, time (a products' age) or the release schedule of firms trigger the price landing for each of the 1195 products in our data set. In this way, we put to an empirical test the theoretical properties of prices discussed in analytical studies and we connect both streams of research.

3 Video-Game Prices

In this section we first describe our data and next we present a brief description of the video-game market.

3.1 Data

The database we analyze consists of monthly time series of unit sales and prices for 1195 PlayStation2 (PS2) video games released between September 1995 and February 2002 in the US. This data was collected by NPD Group from retailers that account for 65% of the US market. We used the first two years of data for each video-game and left out VG's with less than 12 monthly observations. This time frame is justified by the fact that most VG's stay on store shelves for less than two years and their sales drop very rapidly to zero afterwards. Binken and Stremersch (2009) use the same data and they assume that a video-game is in a so-called *dead regime* after its sales drop below 5000 units. Therefore, Binken and Stremersch (2009) do not use any observation after this cut-off point which leaves out 32 % of their observations. In our case the 24 month cut-off point leaves out 38 % of the observations. We compared our results against a 30 and a 36 month cut-off point that leave out 28 and 20 % of the observations, respectively, and our results are qualitatively the same. Our final sample consists of 1075 video-games.

In Figure 1 we show the price landing of 50 randomly selected video-games. This figure clearly shows the great diversity of price patterns but it is easy to see of the common feature across games: their price drops at a certain moment in time. The introductory prices range from 40 to approximately 60 USD while their landing level is between 15 and 30 USD. Similarly, there is great diversity in the timing of price landings. It is easy to notice that some VG's prices drop right after the second month while others land around the 10th, 12th or 15th month or even later. Finally we notice that some prices drop very fast, see the lines almost parallel to the vertical axis, while in many other cases they land at slower rates and with more noise around them.

In Figure 2 we show the price landing of one of the most popular VG's, the Spider-Man game. We plot the price of the Spider-Man game on the vertical axis but in each of the panels we use a different scale on the horizontal axis. In the upper-left panel we use time on the horizontal axis, in the upper right panel we use the cumulative sales of Spider-Man and in the lower panel we use the cumulative number of VG's launched to the market after the introduction of Spider-Man. We choose these axes because later we will identify each of these variables as a potential trigger of price landings. More details on this are given in Section 4.3. These graphs of course show very similar price patterns. That is, we could say that the price cut of the Spider-Man occurred approximately at the 10th month after its introduction (upper-left panel); or just after reaching 600 thousand unit sales (upper-right panel); or after 250 VG's were launched (lower panel). The price landings in these figures are similar but the interpretation of the different thresholds is very different. In all cases, these thresholds represent an event after which prices drop, that is the timing of price landings. Finally, if we look closely at the different price landing patterns we discover that the speed of landing varies across these panels. Prices seem to drop much faster when we use cumulative sales than when we use time on the horizontal axis.

In the analysis that follows we show how we select one of these potential price landing triggers for each of the products in our sample. Specifically, in Section 4.3 we present how we use our mixture specification and the underlying distributions of price landings to select among potentially correlated price landing triggers. Developing a joint model for prices, sales and competitive entry is beyond the scope of this article and we consider it as an area for future research. We explain more details on our modeling approach in Section 4 and in this section we continue with a presentation of the market context of our application.

3.2 The Video-Game Market

The video-game market is highly competitive and there are 78 video-game publishers who design games for PS2. On average, they released 29 new video-games per month between 1992 and 2005. The main publisher of these VG's is Sony and it has a market share of 16%. Acclaim and Electronic Arts follow Sony with market shares of 11% and 6%, respectively. In the upper left panel of Figure 3 we present the distribution of the market shares across all publishers. We notice that 20 publishers have about 80% of the market while the 58 remaining publishers cover the next 20% of the market. In the upper right panel of Figure 3 we depict the monthly time series of the number of newly released video-games. There is an upward trend in the number of VG's being released. In 1996 less than 11 VG's were released per month while in 2002 this volume has increased to 40 monthly releases.

The bottom left panel of Figure 3 shows the industry's sales pattern. Total VG's sales are extremely seasonal and they peak every December when they may reach numbers like 14 million copies. This last number is especially high if we compare it against the 24.1 million units of PS2 consoles sold between 1995 and 2002. Finally, in the lower right panel we show the average number of video-games released from 1995 to 2002 and the average sales per month. An interesting fact is that most new VG's are released during November and January but sales peak in between these two months. From 1995 to 2002, December

VG's unit sales are on average 14 million and in January sales decrease to less than 3 million copies while on average 18 new VG's are released on December, 27 in November and 34 in January. In Figure 4 we can see the distribution of the type of video-games sold. For example, sports games account for 21.5 %, Action 14 % while Strategy games account for 4 % of all VG's in our data.

The consumers in this market concern 40 million US-based consumers who buy video-games each year. Figure 5 shows a histogram of the total sales across all VG's. Preferences clearly differ across VG's as we observe substantial heterogeneity in the market potential across the video-games. We follow the tradition of diffusion research by labeling the cumulative sales reached by a video-game as the market potential. From Figure 5 we can learn that sales above one million units for a single game seem to occur only rarely. The average market potential for the video-games in our sample is around 254.75 thousand units. However, approximately for half of the VG's in our sample (to be precise: for 504 video games) the market potential is less than 66 thousand units.

4 Price Landing: Modeling

In this section we present our modeling approach. The model and econometric approach we present allow us measure quantitatively the theoretical features of prices discussed in our literature review. Specifically, the equation we propose allows us describe the speed and timing of price transitions while we use mixture modeling to test the relative importance of different price landing triggers. Finally, we apply a hierarchical structure to describe the empirical distributions of the timing and speed of price transitions and at the same time to identify the most likely price triggers.

Our model consists of two parts. First we present an equation to describe the price landing, that is the underlying price of product i at time t, which we call $P_i^*(t)$. Next we specify an equation that relates the pricing landing to the actually observed prices, what we call $P_i(t)$. As we observe in Figure 1, prices follow a general inverse S-shape but they do not follow it very smoothly and in most cases the prices we observe are noisy. Hence, in the first equation we capture the price landing and its main two features (timing and speed) and in the second we capture deviations from it. In Section 4.1 we present these two equations. Each video-game is allowed to have its own price landing speed, timing, initial price and landing price parameters. In Section 4.2 we therefore specify how we model this heterogeneity. In Section 4.3 we briefly discuss the mixture specification that allows us to identify the trigger of the price landing for each video-game. In Section 4.4 we discuss heterogeneity in mixture probabilities. In Section 4.5 we present details regarding the co-variates in the hierarchical structure of the model.

4.1 Price Landing Model

The price landing of game i is $P_i^*(t)$ and we assume it depends on a trigger denoted by $D_i(t)$. That is, prices change according to

$$\frac{dP_i^*(t)}{dD_i(t)} = \frac{(P_i^*(t) - \kappa_i)(\rho_i - P_i^*(t))}{(\kappa_i - \rho_i)\nu_i}, \tag{1}$$

where ρ_i is the starting price level, κ_i is the final pricing level, and ν_i a constant that moderates the rate of change $dP_i^*(t)/dD_i(t)$. For ease of interpretation, $D_i(t)$ might be for example time and then $dP_i^*(t)/dD_i(t) = dP_i^*(t)/dt$. $D_i(t)$ can be set to be any trigger variable that we are interested in, like sales or competition. From (1) we see that a smaller ν_i implies a faster rate of change. Here, the time index t will in each case be relative to the launch date of the particular product. In other words for each product $t = 0$ corresponds to the time of launch. In the numerator of (1) we have that the closer $P_i^*(t)$ is to its initial or final levels, the slower prices would change and that if $P_i^*(t) < \rho_i$, $\nu_i > 0$, $P_i^*(t) > \kappa_i$, $\rho_i > \kappa_i$ for all t then $dP_i^*(t)/dD_i(t) < 0$. These last conditions describe very closely the price patterns that are common among high-tech products.

Equation (1) may be unusual in the sense that it models dP/dD instead of dD/dP. However, in our application we will use different trigger variables for D and hence dD/dP

would not have the common interpretation we find in the literature when D are sales; for example, D could be competitive introductions. The former is the typical solution proposed by analytical studies while the latter is the typical form assumed in empirical studies. One of the possible reasons why empirical studies have assumed this latter form is that many of them focus on a single firm, usually a monopolist that sets prices. In contrast, in our study we observe the $\frac{dP_i^*(t)}{dD_i(t)}$ for hundredths of products launched by 78 firms that are price setters. Hence, our objective is to characterize the heterogeneity of $\frac{dP_i^*(t)}{dD_i(t)}$ across products and to capture two of its features, the timing (λ_i) and speed (ν_i) of significant price cuts. In addition, the advantage of equation (1) is that we can solve it analytically and test it empirically. In fact, it can be shown that (1) is a separable differential equation and that its solution is

$$P_i^*(t) = \kappa_i + (\rho_i - \kappa_i)h_i(t), \tag{2}$$

with

$$h_i(t) = 1 - \frac{e^{\left(\frac{D_i(t)-\lambda_i}{\nu_i}\right)}}{1 + e^{\left(\frac{D_i(t)-\lambda_i}{\nu_i}\right)}}. \tag{3}$$

That is, we propose that the price of product i is composed of two parts, a fixed landing price (κ_i) plus a mark-up ($\rho_i - \kappa_i$) that evolves over time proportionally to $h_i(t)$. The function $h_i(t)$ gives the percentage of the markup at time t and it is bounded between 0 and 1. The function (3) for $h_i(t)$ follows a logistic shape and λ_i can be interpreted as the location of the price landing for product i in terms of the trigger $D_i(t)$ while ν_i is the speed at which the landing occurs. That is, we observe a price drop after $D_i(t)$ reaches its threshold λ_i and this is why we call $D_i(t)$ the *trigger variable.*

The advantage of a logistic function for the pricing equation is that we can interpret its parameters in a natural way in our application. We plot equation (1) for $D_i(t) = t$ and different values of λ_i and ν_i in Figure 6. As can be noticed from the graph, the effect of an increase (decrease) of λ_i is to shift the complete function to the right (left) and ν_i has the role of smoothing the function or steepening the function. That is, ν_i is a parameter that determines how fast prices are falling and λ_i captures the moment (event) when prices are dropping.

In principle, $D_i(t)$ can be any variable that increases monotonously. The simplest choice for $D_i(t)$ is simply time ($D_i(t) = t$). It is important to notice that the interpretation of λ_i and ν_i depend on the choice of $D_i(t)$. If we set $D_i(t)$ to be the cumulative sales of product i then λ_i is simply the number of items sold at high prices. We might interpret this limit as a proxy for the size of the segment that buys at high prices; what some call the *hard-core gamer* segment. This is a natural interpretation for λ_i but we do not claim that this model really identifies who and how many are the real *hard-core gamers*. Furthermore, if we define $D_i(t)$ as the number of products introduced after launch of product i then λ_i becomes a competitive threshold after which prices are cut. In all cases ν_i is a scaling constant that marks the transition speed of prices as we set in equation (1) and it of course depends on the scale of $D_i(t)$. Notice that $D_i(t)$ might be a combination of different trigger variables. The interpretation of the λ_i parameters then becomes troublesome with such specification.

As discussed above, $P_i^*(t)$ aims to capture the underlying price pattern of product i, that we call price landing. For actual data we observe this pattern plus noise. The observed prices may therefore differ from $P_i^*(t)$. Furthermore, we only observe the prices at regularly spaced intervals. We adopt the convention that we observe the prices for product i at $t = 0, 1, 2, \ldots, T_i$. We denote the observed price at time t by $P_i(t)$. We model the relation between the observed prices and price landing pattern using a first order auto-regressive specification. In terms of the observed price this gives

$$P_i(t) = P_i^*(t) + \alpha_i[P_i(t-1) - P_i^*(t-1)] + \varepsilon_i(t) \qquad t = 1, 2, 3, \ldots, T_i, \tag{4}$$

where $\varepsilon_i(t)$ denotes the source of the random deviation at time t from the underlying price landing pattern, and α_i determines the memory in the deviations from the underlying pattern. We assume that $\varepsilon_i(t) \sim N(0, \sigma_i^2)$ for $t = 0, 1, \ldots, T_i$. If $\alpha_i = 0$ there is no memory, and (4) then states that the deviations are independent over time. If $\alpha_i > 0$, a positive deviation at time t is likely to induce a positive deviation at time $t+1$. For the first observation we set

$$P_i(0) = P_i^*(0) + \sqrt{\frac{1}{1-\alpha^2}} \times \varepsilon_i(0). \tag{5}$$

The variance factor is set such that the variance of the random term equals the unconditional variance of $P_i(t)$ in (4).

4.2 Heterogeneity in Main Parameters

In the above discussion of the model we have explicitly allowed for heterogeneity, that is, all parameters and the price cut trigger $D_i(t)$ are product-specific. In this section we discuss how we model the heterogeneity in all parameters.

In the model we will allow for K different triggers, which are denoted by $D_{1i}(t)$, $D_{2i}(t)$, ..., $D_{Ki}(t)$. The relationship between the observed price and the price landing in (2) remains unchanged. In addition, we define a different price landing equation $P_{ki}^*(t)$ for each trigger variable k, that is,

$$\begin{aligned} P_{ki}^*(t) &= \kappa_i + (\rho_i - \kappa_i) h_{ki}(t) \\ h_{ki}(t) &= 1 - \frac{e^{\left(\frac{D_{ki}(t)-\lambda_{ki}}{\nu_{ki}}\right)}}{1+e^{\left(\frac{D_{ki}(t)-\lambda_{ki}}{\nu_{ki}}\right)}}. \end{aligned} \tag{6}$$

Note that this definition is very similar to that in (2) and (3). However, the parameters λ_{ki} and ν_{ki} are now trigger (k) and product (i) specific. Note that the price starting and landing level ρ_i and κ_i are the same across all k possible triggers.

The landing level (κ_i), the initial price level (ρ_i), the threshold value (λ_{ki}) and the speed of adjustment (ν_{ki}) are defined to vary across products. For each of these parameters we specify a second-level model. For the price landing level and the launch prices we specify

$$\begin{aligned} \kappa_i &= Z_i'\gamma^\kappa + \omega_i^\kappa \\ & \qquad\qquad\qquad\qquad \text{with } (\omega_i^\kappa, \omega_i^\rho) \sim N(0, \Sigma), \\ \rho_i &= Z_i'\gamma^\rho + \omega_i^\rho \end{aligned} \tag{7}$$

where Z_i denotes a vector of dimension M of product specific characteristics, γ^κ and γ^ρ are coefficient vectors (dimension $M \times 1$) common across all i products. The error terms ω_i^κ and ω_i^ρ are assumed to be normal with mean 0 and covariance matrix Σ. The Z_i in our model will include mainly product type, manufacturer variables and seasonal dummies. We define the Z_i variables with more detail in Section 4.5. We specify a similar form for the speed and timing parameters. That is, for each trigger variable k we define

$$\begin{aligned} \ln \lambda_{ki} &= Z_i'\gamma_k^\lambda + \eta_{ki}^\lambda \\ & \qquad\qquad\qquad\qquad \text{with } (\eta_{ki}^\lambda, \eta_{ki}^\nu)' \sim N(0, \Omega_k). \\ \ln \nu_{ki} &= Z_i'\gamma_k^\nu + \eta_{ki}^\nu \end{aligned} \tag{8}$$

where η_{ki}^λ and η_{ki}^ν are the error terms and they are assumed to be normal with mean 0 and covariance matrix Ω_k. The γ_k^λ and γ_k^ν are coefficients vectors (dimension M) and Z_i are the same group of group of covariates as in the equations for κ_i and ρ_i. The log transformation in (8) is used to ensure that λ_{ki} and ν_{ki} are positive. If it is the case that the timing and the speed of price landings are correlated we will capture this correlation with the matrix Ω_k. For example, it might be that when prices fall at a slower rate (ν_i^k) they are cut at an earlier time (λ_i^k).

4.3 Choice of Trigger and Mixture Specification

The actual trigger of the price landing for each product is of course unobserved to the *researcher*. We denote this (unobserved) variable as S_i, that is, we denote $S_i = k$ if the trigger variable k is selected for product i. We complete this part of the model by specifying probabilities for each trigger, that is, the trigger k is selected with probability

π_k for $k = 1, 2, \ldots, K$. In our application $k = 1$ would mean that *time* is the trigger, $k = 2$ means that *cumulative sales* are the trigger and $k = 3$ means that *cumulative competitive introductions* are the main trigger of equation (2). In the four-trigger version of our model $k = 4$ means that the release schedule of firms are the main trigger. We provide more details on how we measure each trigger variable in subsection 4.5. The probabilities π_k will reflect the overall likelihood of each of the different triggers. However, note that conditionally on the observed prices, the probability of $S_i = k$ is different across games.

It is important to note that the trigger variables might be correlated with each other in time but this correlation does not prevent the identification of the more likely trigger for each video-game. The reason is that we aim to identify the distribution of the game-specific thresholds for each trigger variable and the game-specific threshold after which prices land. For example, the price landings of video-games might occur, according to its distribution, around the sixth month after launch but the sixth month represents many different levels of cumulative sales for the video-games in our sample. It might be that some video-games sold in total 10 thousand units during these six months while other video-games sold more than 500 thousand units. That is, the time correlation between trigger variables does not necessarily translate into a correlation between the game-specific thresholds that we are aiming to identify.

In Figure 7 we describe the intuition about how triggers are selected and statistically identified. For this purpose we need two main elements. The first element consists of the distributions of the threshold parameters for each of the different triggers. That is, the distribution of λ_{ki} and ν_{ki} across all i and for each k. For example, if we collect the parameter λ_{1i} for all i we obtain the distribution of λ for the first trigger variable. As we defined in equation (8), the distribution of λ_{ki} and ν_{ki} depend on co-variates Z_i and hyper-parameters γ_k and the variance term associated to them. The second element we need is the match between the price landing of game i and the distributions of λ_{ki} and ν_{ki} for $k = 1, \ldots, K$.

In Figure 7 we plot again the price of the Spider-Man. In addition, we plot a hypothetical distribution of the threshold parameters λ_{ki} for each of the mixture components k. The distribution of λ_{1i} in the upper left panel, λ_{2i} in the upper right panel and λ_{3i} in the lower left panel. Note that λ_{1i} is the time (in months) after which the price drops (if $D_i(t)$ is time, that is when $k = 1$). In the same way, if $D_i(t)$ is cumulative sales then λ_{2i} is the cumulative number of sales after which the price drops and λ_{3i} is the cumulative number of competitive introductions after which the price drops when $D_i(t)$ amounts to competitive introductions. We notice that the $\hat{\lambda}_{1i} \approx 11$ months, that $\hat{\lambda}_{2i} \approx 600$ thousand units and that $\hat{\lambda}_{3i} \approx 250$ units. Given the λ_{ki} thresholds we can now compare them against the corresponding distributions. In this case we see that the $\hat{\lambda}_{2i}$ is the closest to the mode of its corresponding distribution. Hence, the most likely trigger of the Spider-Man price landing is sales. The least likely trigger is competition and next is time. Of course, in our model we take into account the distribution of λ_{ki} and ν_{ki} simultaneously when we draw the most likely trigger for each video-game in our sample. All technical details about trigger selection are given in the Appendix A. Next we describe how we model heterogeneity in the mixture components.

4.4 Heterogeneity in Mixture Probabilities

We suspect that there also might be heterogeneity in the mixture probabilities across games. For example, the games of some publishers may be more likely to belong to the time mixture. Hence, as an extension to the model we allow the probabilities of $S_i = k$ to depend on a set of product specific variables. To model this dependence we specify a Multinomial Probit Model for S_i. Hence, we introduce additional latent variables y_i^* for $i = 1, \ldots, N$ and $k = 1, \ldots, K$. These latent variables are related to S_i by

$$S_i = k \quad \text{if and only if} \quad y_{ki}^* = \max_{l=1\ldots K}(y_{li}^*). \tag{9}$$

We specify y_{ki}^* as

$$y_{ki}^* = Z_i'\delta_k + \vartheta_{ik} \quad \text{with} \quad \vartheta_i \sim N(0, I), \tag{10}$$

where $\vartheta_{\mathbf{i}} = (\vartheta_{1i,}\vartheta_{2i,}, ..., \vartheta_{Ki})$ and we set $\delta_1 = 0$ for identification. In principle the set of variables used in this specification may differ from that in (6) and (7). The probability that the trigger k is used for product i now becomes

$$\pi_{ki} = \Pr[y^*_{ki} = \max_{l=1...K}(y^*_{li})]. \tag{11}$$

This concludes our model specification. For inference we will rely on MCMC and Bayesian analysis and treat all product specific parameters as latent variables and we sample these together with the parameters in (6), (7) and (8). A complete description of the sampling steps in this Markov Chain can be found in the Appendix A.

4.5 Model Specifics for Video-Games Pricing Model

We consider two versions of our model. The first version uses three trigger variables and the second uses four trigger variables. We define $D_{ki}(t)$, for $k = 1, 2, 3, 4$ where $D_{1i}(t) = A_i(t)$, $D_{2i}(t) = C_i(t)$ and $D_{3i}(t) = I_i(t)$ and $D_{4i}(t) = R_i(t)$. $A_i(t)$ is defined as the age of a video-game in months, that is, the time between launch and t. $C_i(t)$ is the cumulative sales of video-game i between release date and t. $I_i(t)$ is defined as the cumulative number of video-games introduced between the launch date of video-game i and t. $R_i(t)$ is defined as the release schedule of the firm that released product i. We know the number of games a firm released at every point in time. To create $R_i(t)$, we use a time window that sums the introductions from the introduction of game i up to the next three months after t.

The interpretation of λ_{ki} and ν_{ki} varies depending on the trigger k. Hence, λ_{1i} can be interpreted as the price landing time, λ_{2i} as a competitive threshold, λ_{3i} as the hard-core gamer segment size and λ_{4i} as a release limit after which we observe a price drop. For each of these triggers, the parameter ν_{ki} for $k = 1, 2, 3, 4$ can be interpreted as a scaling constant that changes the speed at which the price landing occurs.

In all what follows in this section we focus on the model with three triggers, that is $k = 1, 2, 3$ and we leave out $R_i(t)$. The reason for this is that $R_i(t)$ is selected with a probability very close to zero when we include it as the fourth trigger variable. We present the discussion regarding the fourth trigger in our results in section 5.2.

The hierarchical structure of the corresponding threshold λ_{ki}, speed ν_{ki} and ρ_i and κ_i parameters for each mixture component will depend on a set of Z_i variables that contain game type, publisher and seasonal effects plus the launch price and the time to the introduction of a new game consoles as co-variates. Seasonal dummies are defined by the month of launch of each video-game i. The launch price is the observed price of video game i at launch time, that is at $t = 0$. We include this variable in order to test if our co-variates remain significant after including past prices in the equation for the timing and speed of launch. It might be that the price at launch of a VG might contain information regarding the timing of the price landing and its speed. In addition, we believe it is reasonable to include the launch price because of the very likely uni-directional relationship between launch price and timing of price landing. That is, it is very hard to argue that a firm decides how to price a VG's based on its decision on when to permanently cut its price; on the other hand, it might be that firms decide to cut prices based on the launch price. For example, firms might cut the price of expensive games after longer time than the time they wait to cut the price of cheaper VG's. Moreover, the launch price is a proxy for quality and hence we test if our covariates remain significant after we control for them.

The time to console launch measures the time (in months) between a video-game release and the launch of the VG's console that is being released after the video-game introduction. For example, the PlayStation2 with DS controllers was introduced in June 1998 and other versions of the PS2 console were released in February 1999 and January 2002. This means that a video-game released in January 1998 will face a console introduction after 6 months; a video-game released in January 1997 will face a release in 18 months, and so on. For each video-game we calculate the time between its release and the forthcoming console at the video-game release date. We include this variable to test whether the price landing pattern varies relative to the release date of video-game consoles. Our results do not significantly change if we leave both time to console launch and launch price out of the Z_i covariates.

From the seasonal fixed effects we excluded January, from the game types we excluded Adventure games. The remaining game type categories are: Action, Arcade, Children, Driving, Family, Fighting, Role playing, Shooter, Sports, Strategy and Compilations. The remaining publisher dummies are Electronic Arts, Acclaim, Infogames, Konami, Activision, Midway, Eidos Interactive, THQ, Capcom, Namco, Agetec, Interplay, Hasbro, 2nd group, 3rd group and 4th group. The 2nd group is composed by six publishers that each have at least 1% market share, the 3nd group is composed by 14 publishers that account for the next 10% market share and the 4th group is composed by 43 publishers that account for less than 1% of the market share in total. In all our tables we sorted publishers by their market share and in descending order. The main publishers (EA, Acclaim, etc.) account for 80% of the VG's in our sample while the dummies for 2nd, 3rd and 4th publishers group the next 20% of the market share. We set Sony as the reference publisher.

5 Results

In this section we present our results in three subsections. In the first we present results regarding the heterogeneity of the parameters. Next we present the results regarding trigger selection and finally we discuss the model performance.

5.1 Heterogeneity of Landing Time and Speed

Our results indicate that there indeed exists heterogeneity in the model parameters. The first contribution we have to offer is that we find significant firm effects on both the timing and speed parameters across all mixtures. That is, firms might be deciding not only on when to cut the price but also on how fast to cut it. To our knowledge, this result is new and we are the first to show it empirically. In Table 2 and in Table 3 we can see the different firm effects across mixtures and model parameters. For example, Acclaim's landing time (λ_i) coefficient in the time mixture is -0.196 and this means that VG's of Acclaim face a price drop 17.8% earlier relative to Sony. In addition, we find several of the firm effects on the landing speed (ν_i) to be significant. For example, Electronic Arts has a ν that is 91.7 % higher than Sony while Agetec has a slower landing speed with a ν parameter that is 3.81 times higher than Sony. An interesting feature of the time mixture parameters is that most of the firm effects $log(\lambda_{1i})$ are negative while the firm effects for the $log(\nu_{1i})$ are positive. That is, it seems that the video-game prices of most firms are cut at earlier dates than Sony but most firms cut prices at slower speed relative to Sony.

In the last four columns of Table 3 we report the results for the hierarchical specification of the initial and landing price levels, (7). In both cases we observe very important firm effects. For example, Konami sets the landing prices 2.535 USD above the landing prices of Sony, 17.34 USD, while the launch prices of Konami are not significantly different than those of Sony that start at 40.49.

We give a histogram of the posterior mean of the game-specific parameters of the three-mixture model in Figure 8, Figure 9 and for the auto-regressive term of equation (4) in Figure 10. The dispersion in the timing and speed parameters is reported in Figure 9. We can see that each mixture has quite different thresholds and speeds. For example, the time mixture mean is around 7 months. That is, firms cut VG's prices mainly in the 7th month after their release. The timing parameters for all mixtures are graphed in the left frames while in the right frames we present the speed parameter distribution. We note that if the speed parameter ν_i is close to zero then prices fall more steeply. From the histograms in the right panels of Figure 9 we see that several products face sharp price cuts. In addition, in Figure 8 we see the distribution of the starting price level ρ_i for all i in the left frame and the distribution of the κ_i in the right frame. These parameters show that the starting level might be as low as 20 USD and as high as 70 USD while the landing level is as low as 5 USD and as high as 35 USD.

In summary we find that firm effects are important to describe the price landing timing and to describe its speed, the launch and the landing prices of the VG's in our sample. Seasonality is more important for the starting and landing levels of prices and less so for the price landing timing and speed. We also find that for some mixtures the effect of the launch price and the time to launch a new console are significant for some of the main parameters.

5.2 Triggers of Price Landings

Our second contribution is that we find that the triggers that best describe price landings are competitive introductions and time and not cumulative sales. In Figure 11 we report a histogram of the posterior probability of each of the triggers across all games in the three-mixture version of our model.

The academic convention is that sales should be a main price driver. In contrast, we find that the sales indicator is the least likely trigger variable of price landings and it is useful to explain only a 12% of the video-games in our sample. Note that we do not go against the academic convention that posits that sales are a price *driver*. Our results only indicate that sales are not the main price landing *trigger*. Furthermore, we find that the competition indicator, measured by competitive VG's introductions, is the likely trigger of price landings of approximately 25.7% of the VGs in our sample. The study of Nair (2007) finds no evidence of important substitution patterns between video-games and hence he suggests that competition, at the game-specific level, is not important to explain video-game prices. Our model cannot provide insights regarding the individual level competition between different video-games but we find that competition, measured as the cummulative sum of VG's introductions, is a likely trigger of price landings. Finally, we find that the most likely trigger is time itself or in other words, the most probable trigger is simply the *age* of a video-game. The time mixture has a posterior mean probability of 62.21%.

In the fourth-mixture version of our model we tested a fourth trigger without much success. The additional mixture included the release schedule of firms as trigger. The idea was to test whether firms release schedule could have a large probability relative to the other three trigger variables. Firms usually have information on the dates that their new VG's are to be released and therefore the prices of their previously released VG's could depend on the dates of these new introductions. Our data include the number of games each firm released at every point in time and therefore we also know the number of games each firm will release after each point in time. Hence, we sum the VG's introductions before time t up to the introductions in the next three months after t and this sum is the value of $D_i(t)$. Note that $D_i(t)$ is then the release schedule of the manufacturer of the video-game i at time t. We decided to use a three-months time window because most online sources of VG's releases cover, as a maximum, the upcoming three months. Of course, in our database we just know the release schedule perfectly. However, our results indicate that the probability of this latter trigger mixture is on average very close zero. Our conclusion is that price landings are better described by the entire market introductions rather than the release schedule of any single firm. This makes some sense given that the 78 VG's firms in our sample face on average 29 releases per month. Consequently, firms might be more likely to monitor all market introductions rather than their own product introductions.

5.3 Model with Hierarchical Specification in the Mixture Probabilities

We estimate the same specification of our model but now we add a hierarchical specification in the mixture probabilities. In this section we discuss the estimates of this hierarchical specification and in the Appendix A we provide its technical details.

The estimates of the parameters in the hierarchical structure of the mixture probabilities are reported in Table 4. In contrast with the heterogeneity in the main parameters we do not find substantial heterogeneity in the mixture probabilities. For example, we find only three significant publisher effects (Konami, Activision, Midway) in the latent utility of sales and two significant publisher effects (Capcom and Interplay) in the latent utility of the time mixture. That is, we know that there is heterogeneity in the timing and speed of price landings but we do not know why a trigger is more likely than the others. We consider this an area for further research.

5.4 Model Performance

We compare the out-of-sample performance of our model against two models: A naive model for prices, that is an AR(1), and against an alternative version of our model. In this alternative model we use the same specification and parameters and the same number of mixtures as our model but we replace all triggers with time. That is, $D_i(t) = time$ for all k mixture components. We randomly selected 50 video-games and used their first six observations to forecast their complete series. That is, only the first six observations of these 50 games were used for parameter estimation while we continue to use all observations for all other games. These comparisons are reported in Table 5 and in Table 6.

Our model preforms extremely well when compared against the AR(1) model and reasonably well when compared against the restricted model. In Table 5 we see that our model forecasts prices better than a naive AR(1) model for 40 out of the 50 randomly chosen games. We report the root mean square forecast error and the log of the predictive density for all 50 VG's. More details on how we compute the predictive density are given in the Appendix A. Moreover, our model performs better than the model with three time mixtures for 19 out of the same 50 games and in 18 other cases it performs equally well as the alternative specification. In total 37 out of 50 games our specification performs at least as well as the alternative or better. This means that there is information contained in past sales and the competition mixtures that increase our model fit.

The AR(1) model does not capture the timing of significant price cuts and the speed at which the price cut occurs while our model captures these significant price cuts. Nonetheless, the assumption that prices follow an AR(1) pattern is common in previous marketing literature and our evidence suggests that this model performs poorly. The main reason is that new products face significant price cuts during their life-cycle and hence the AR(1) is not a suitable specification for such price patterns. At the moment and to our knowledge, we are the first to propose an empirical model that captures these price dynamics.

The results we presented in the previous sections are robust to different model specifications. For example, we estimated the model without the hierarchical specifications of all its parameters and the price landing timing and speed parameters stay about the same. Furthermore, we estimated the model without the auto-regressive structure in (4) and (5), and again the main parameters are estimated similarly. A reason why our results stay the same is that the pricing equation in (2) can accommodate many different pricing patterns with only four parameters and that we let these parameters to be product-specific. These four parameters are the initial and landing price levels, ρ_i and κ_i, and the timing and speed of price landings, the λ_i and ν_i.

6 Conclusions

Our aim with this article was to model the dynamics of new product price landing patterns. Price landings usually follow the inverse of the well known S-shape of sales. Nonetheless, we found no empirical studies dealing with these regularities of new product prices.

In this article we were concerned with products that face one significant price cut during their life cycle. Several online price trackers report similar dynamics to a wider range of products like mobile phones, cameras, storage media, books, etc. Our data was collected by NPD Group but several websites like www.pricescan.com or www.streetprices.com let their users plot price trends and indeed it is relatively easy to find many other products facing a single and significant price drop during their lifetime. We believe that knowing when a price is cut or when to significantly cut the price of a product permanently is an exciting area of further research and one with wide managerial implications across different industries.

In this article we provided evidence that there is heterogeneity both in the timing and speed of price landings. We found that most of this heterogeneity is driven by firm effects. Our model captures this heterogeneity and it is flexible and useful to forecast and describe the price landing patterns in our data. Finally, we found that it is the age of a video-game that is triggering the price landings. The next most likely trigger is competition and the least likely is cumulative sales. This latter finding goes against the academic convention that sales are the main *driver* of prices. At least for our application we found convincing evidence that sales are not the most likely *trigger* of significant price cuts.

7 Figures and Tables

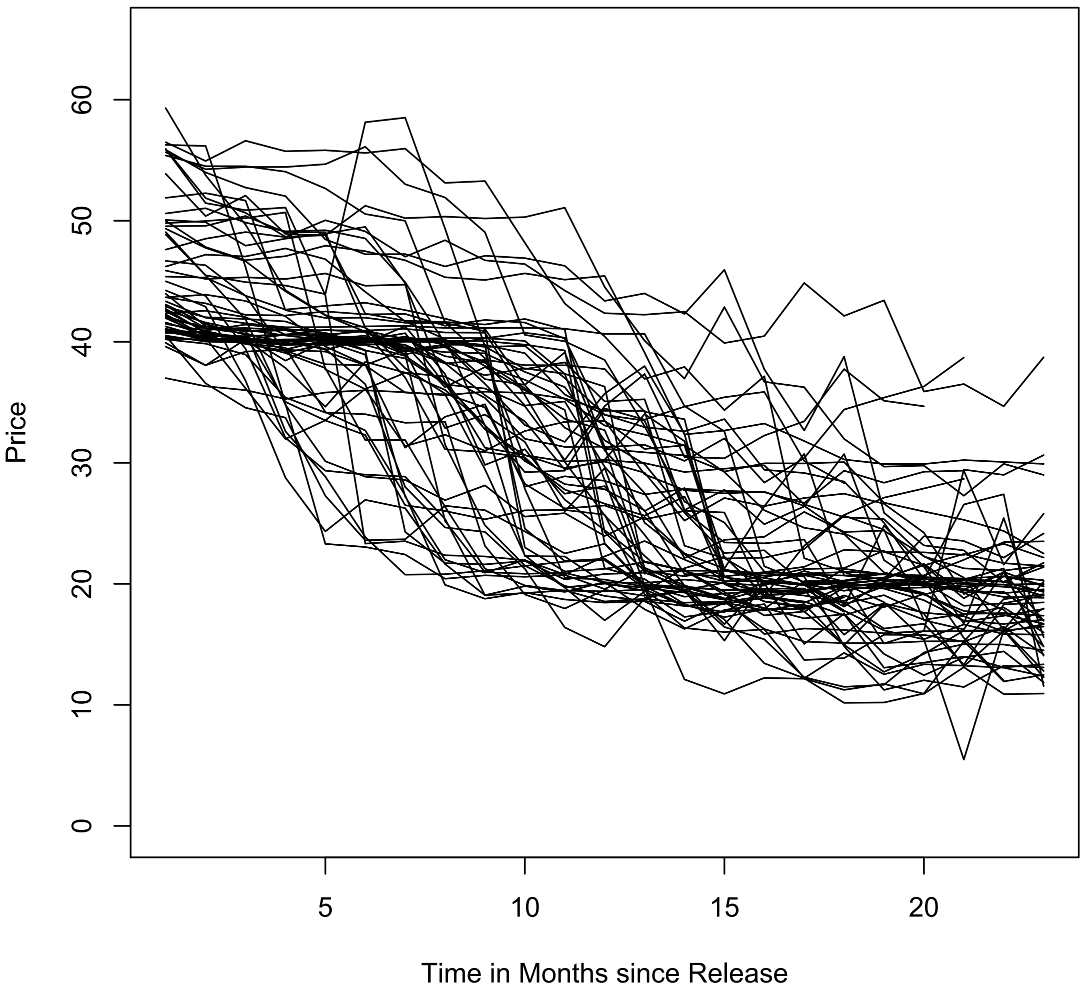

Figure 1: Price Landing Pattern for 50 Randomly Selected Games

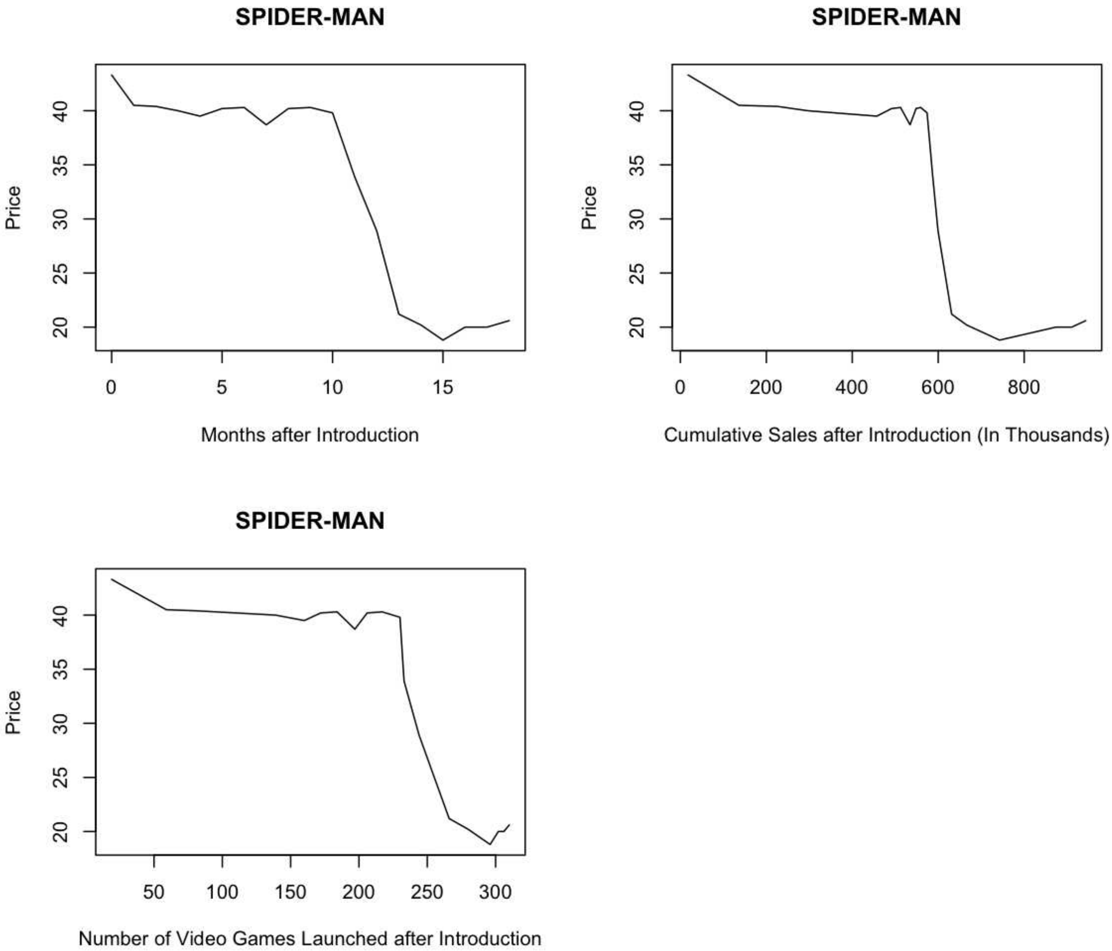

Figure 2: Typical Price Landing Pattern

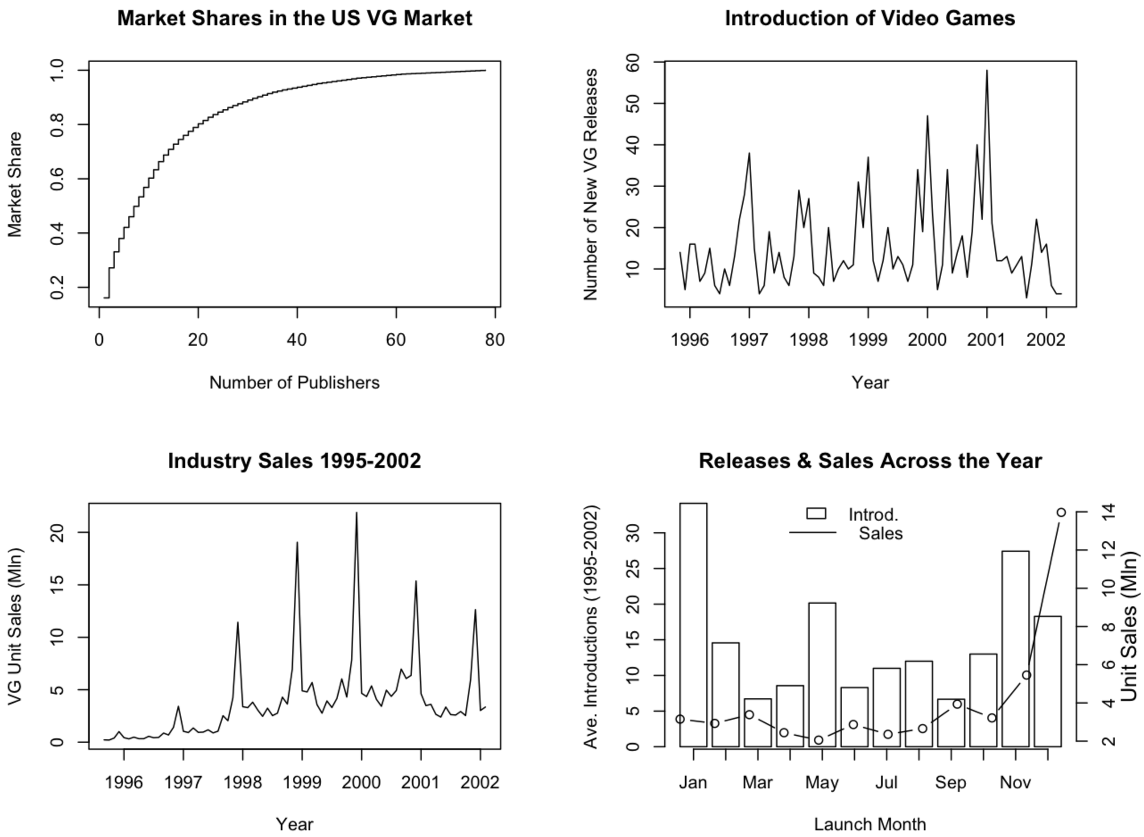

Figure 3: The Video-Games Market

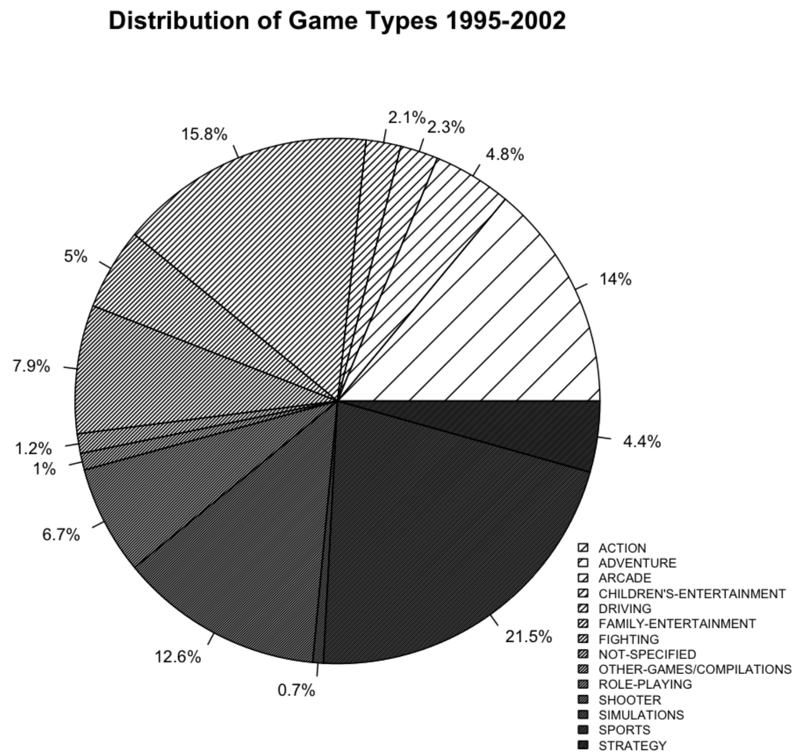

Figure 4: What do publishers sell?

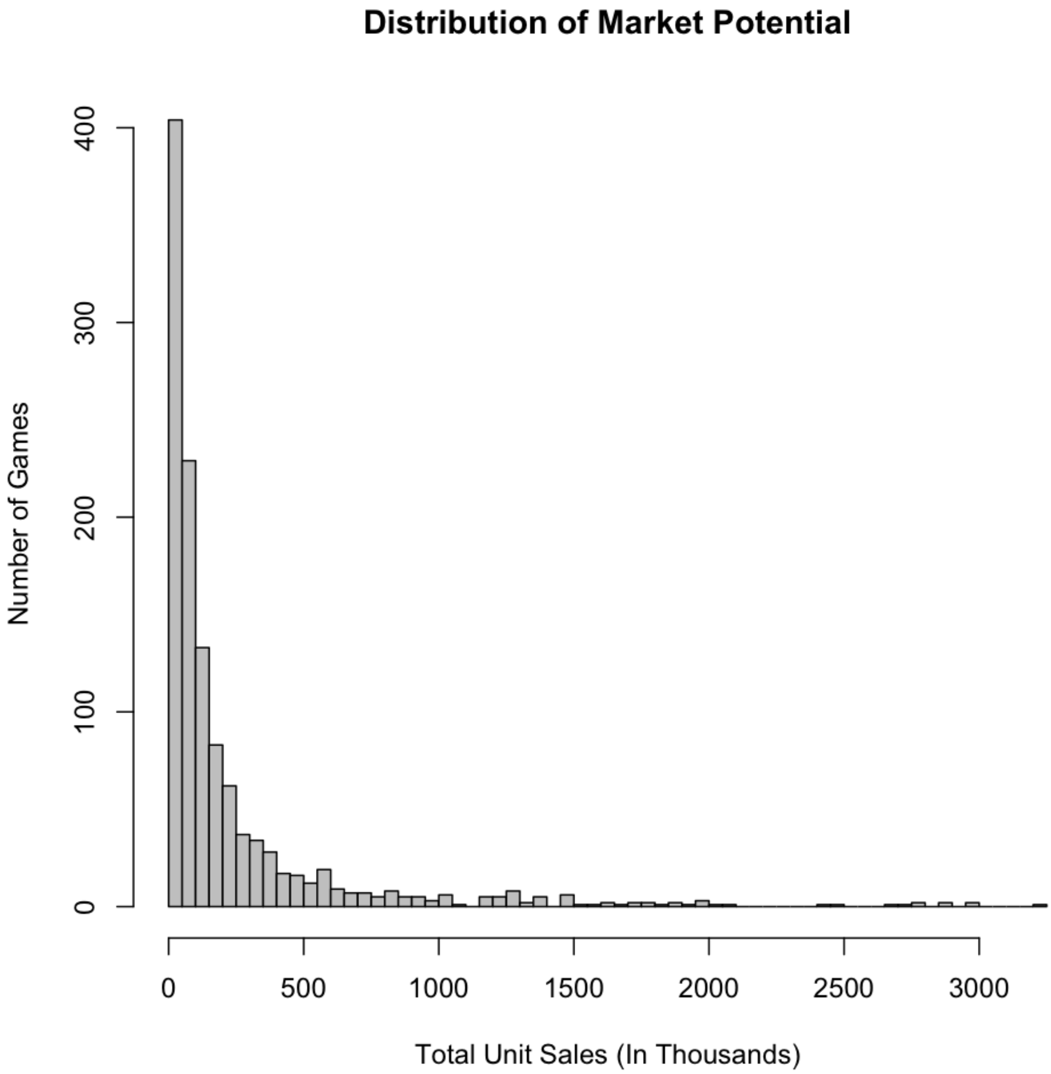

Figure 5: Total Sales Distribution

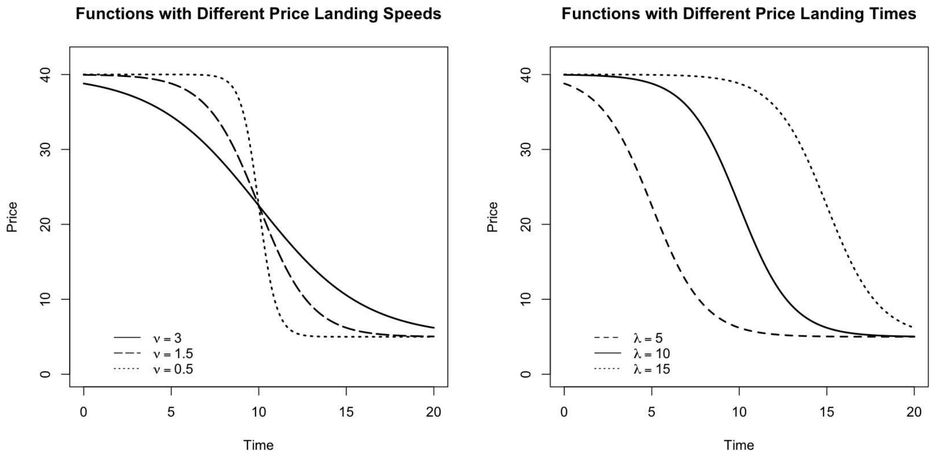

Figure 6: Main Pricing Function at Different Parameter Values

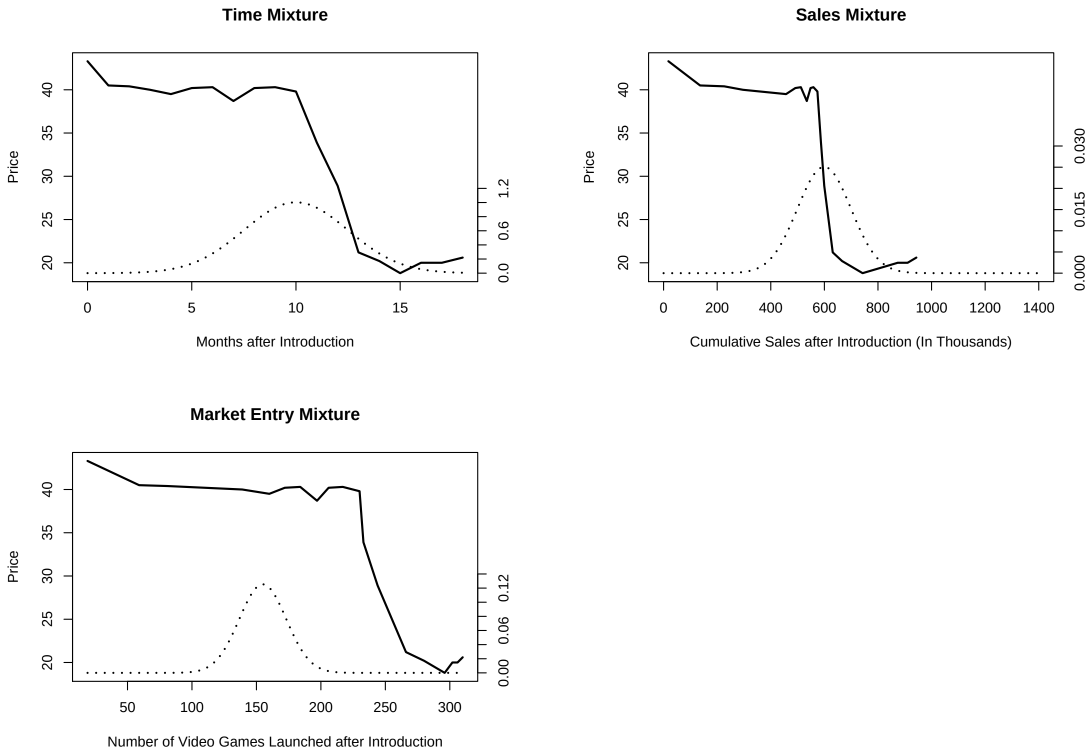

Figure 7: Identification of Triggers

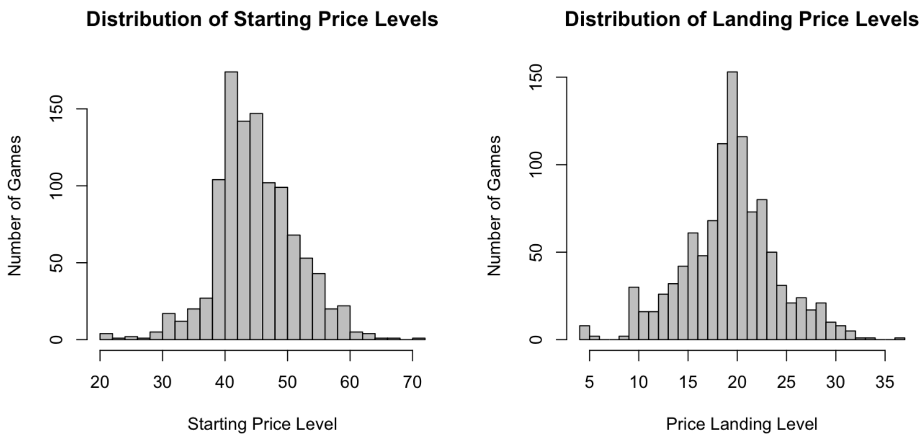

Figure 8: Histogram of the Posterior Mean of Starting (ρ_i) and Landing Price (κ_i) Parameters

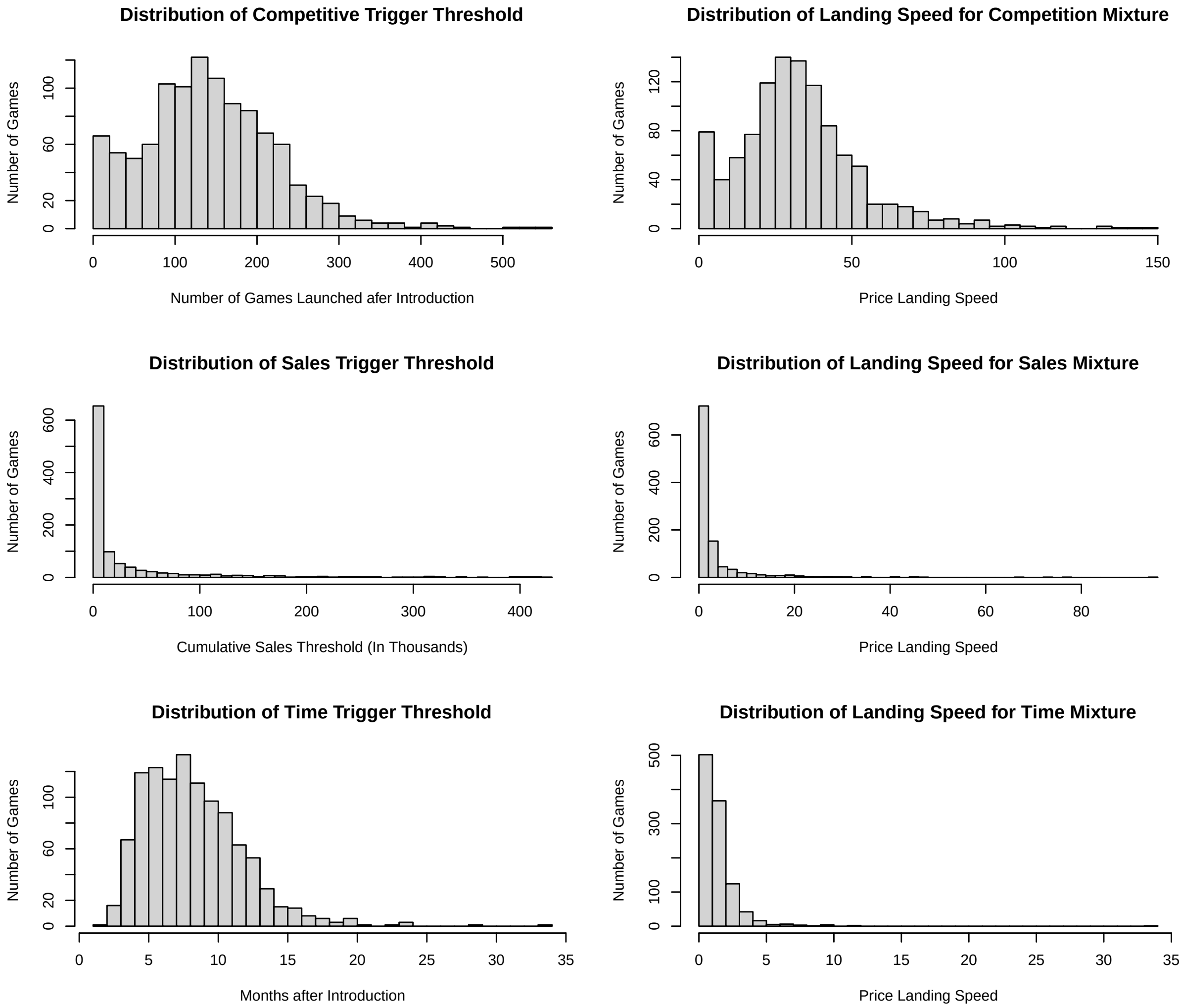

Figure 9: Histogram of the Posterior Mean of the Threshold (λ_i^k) and Speed (ν_i^k) Parameters

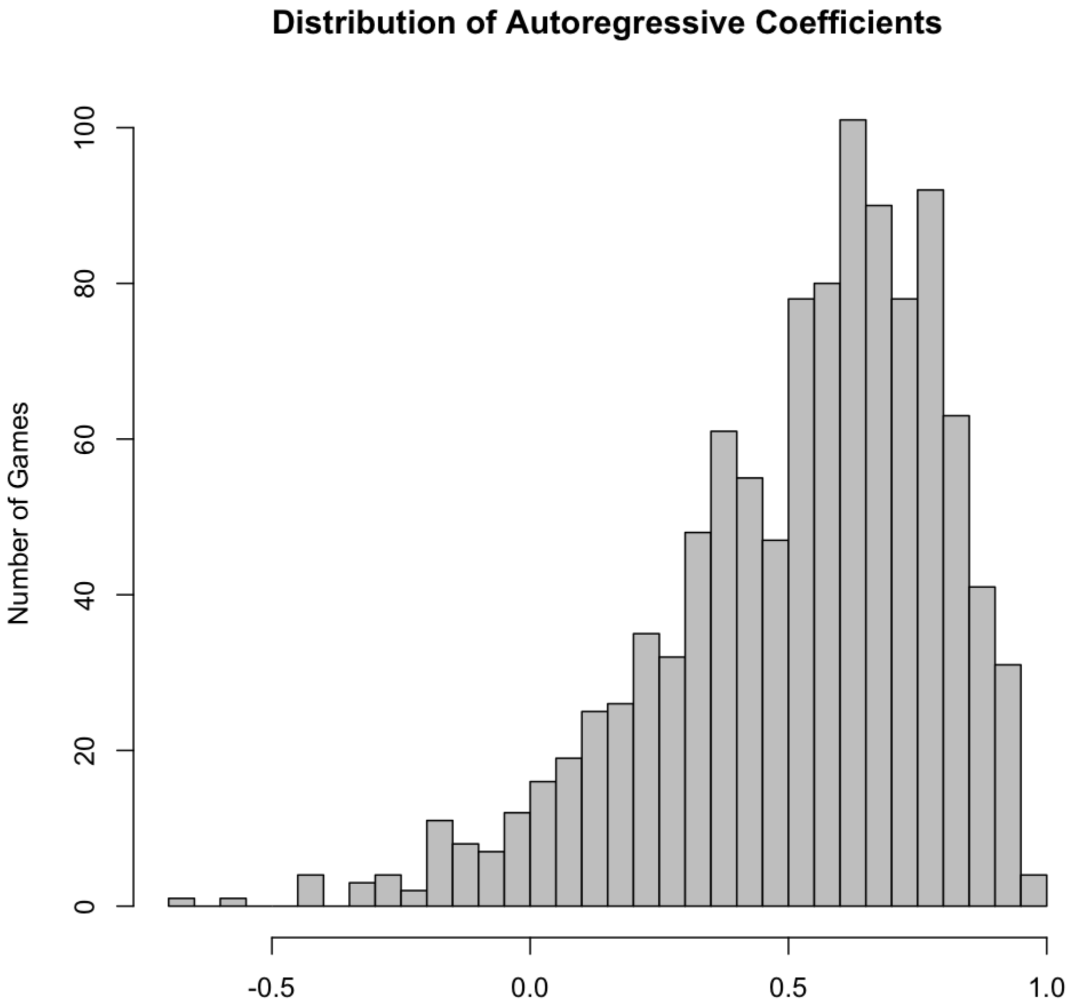

Figure 10: Histogram of the Posterior Mean of the α_i Parameters

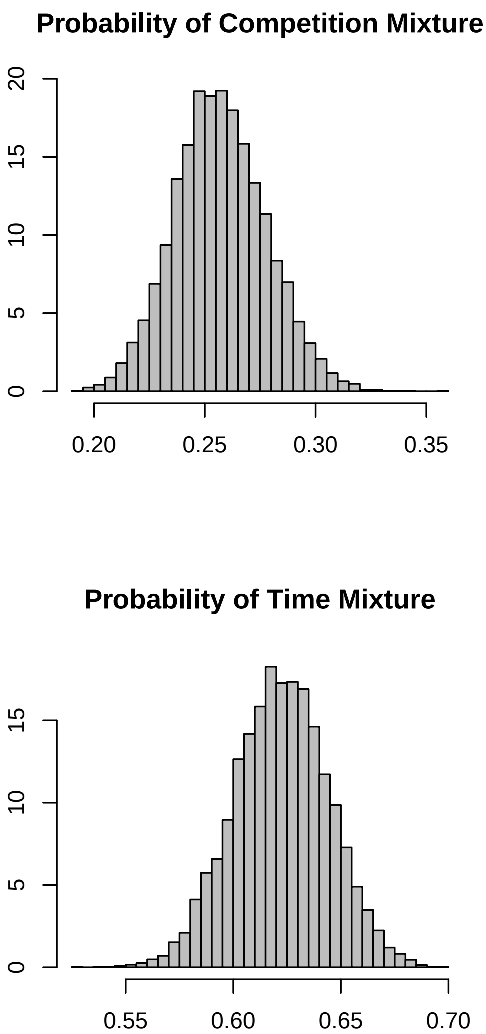

Figure 11: Histogram of the Posterior Mean of the Price Triggers Probability $P(S_i = k)$

NEW PRODUCTS PRICING STUDIES					
Author (Journal, Year)	**Approach**	**Price Change Speed**	**Price Mimics Diffusion**	**When to cut prices**	**Main Price Driver**
Bass and Bultez (1982)	Analytical	–	Yes	No	Saturation
Bayus (1994)	Empirical	Gradual	No*	No	Saturation
Bayus (1992)	Analytical	Gradual	Maybe*	No	Learning Curve + Consumer Heterogeneity + Entry
Clements and Ohashi (2005)	Empirical	Gradual	No	No	Saturation + Indirect Network Effects
Chintagunta et al. (2009)	Empirical	Gradual	No	No	Saturation + Marketing Mix
Dockner and Gaunersdorfer (1996)	Analytical	Gradual	No*	No	Saturation + Entry
Dockner and Jorgensen (1988)	Analytical	Gradual	Yes*	No	Learning Curve + Saturation
Dolan and Jeuland (1981)	Analytical	Gradual	Maybe*	No	Learning Curve
Eliashberg and Jeuland (1986)	Analytical	Jumps	No*	No	Entry
Feng and Gallego (1995)	Analytical	Jumps	No	Yes	Saturation
Ferguson and Koenigsberg (2007)	Analytical	Jumps	No	Yes	Deteriorating Inventory
Franza and Gaimon (1998)	Analytical	Gradual	No	Yes	Entry Timing + Saturation + Learning Curve
Gupta and Di Benedetto (2007)	Analytical	Gradual	No	Yes	Entry + Advertising
Gupta et al. (2006)	Analytical	Jumps	No	Yes	Deteriorating Inventory + Consumer Valuations
Horsky (1990)	Empirical	Gradual	Yes*	No	Saturation
Kalish (1985)	Empirical	Gradual	No	No	Advertising
Kalish (1983)	Analytical	Gradual	Yes*	No	Learning Curve + Saturation
Kalish and Lilien (1983)	Analytical	Gradual	Yes*	No	Saturation
Kornish (2001)	Analytical	Gradual	No*	No	Entry (New Product Generations)
Krishnan et al. (1999)	Analytical	Gradual	No	Yes	Saturation
Nair (2007)	Empirical	Jumps	No	Yes	Consumer Heterogeneity + Expectations
Nascimento and Vanhonacker (1993)	Analytical	Gradual	No	No	Consumer Heterogeneity + New Product Generations
Padmanabhan and Bass (1993)	Analytical	Jumps	No	Yes	Entry + New Product Generations
Parker (1992)	Empirical	–	No	No	Saturation
Rajan et al. (1992)	Analytical	Jumps	Yes	Yes	Saturation
Rao and Bass (1985)	Analytical	Gradual	Yes	–	Learning Curves + Saturation
Raman and Chatterjee (1995)	Analytical	Gradual	Yes	No	Saturation
Robinson and Lakhani (1975)	Analytical	Gradual	No*	No	Saturation
Schmalen (1982)	Analytical	Jumps	No	No	Entry
Simon (1979)	Empirical	Gradual	No	Yes	Saturation
Teng and Thompson (1996)	Analytical	Jumps	No	Yes	Saturation + Quality
Zhao and Zheng (2000)	Analytical	Jumps	No	Yes	Consumer Heterogeneity

Note: *The study supports price skimming

Table 1: Literature Review on New Products Pricing

	Mixture (1) D(t)= VG's Age				Mixture (2) D(t) = Cumulative VG's Introductions			
	Landing Time $log(\lambda_i)$		Landing Speed $log(\nu_i)$		Competitive Threshold $log(\lambda_i)$		Landing Speed $log(\nu_i)$	
Intercept	**1.887*****	(0.266)	-0.575	(0.627)	**1.273*****	(0.389)	**2.419****	(0.914)
Game Type								
Action	**-0.234***	(0.122)	-0.172	(0.307)	-0.050	(0.205)	-0.197	(0.378)
Arcade	-0.248	(0.186)	-0.715	(0.500)	-1.909	(1.517)	-2.508	(2.354)
Children	-0.266	(0.217)	-0.250	(0.526)	0.380	(0.286)	**-1.575****	(0.695)
Driving	**-0.350****	(0.133)	-0.400	(0.334)	-0.308	(0.195)	-0.200	(0.393)
Family	**-0.378****	(0.178)	0.459	(0.417)	**0.504***	(0.281)	-0.602	(0.529)
Fighting	**-0.295***	(0.145)	-0.120	(0.347)	-0.218	(0.224)	-0.607	(0.543)
Role playing	-0.056	(0.143)	-0.493	(0.381)	-0.060	(0.207)	-0.060	(0.502)
Shooter	**-0.646*****	(0.134)	-0.006	(0.334)	-0.182	(0.188)	-0.085	(0.357)
Sports	**-0.276****	(0.123)	-0.249	(0.313)	-0.096	(0.179)	-0.056	(0.382)
Strategy	-0.269	(0.176)	-0.383	(0.393)	-0.142	(0.212)	-0.329	(0.470)
Compilations	-0.342	(0.220)	**1.116****	(0.503)	**-2.450*****	(0.473)	**-5.903*****	(1.389)
Publisher								
Electronic Arts	-0.014	(0.079)	**1.226*****	(0.211)	-0.220	(0.133)	-0.022	(0.298)
Acclaim	**-0.196***	(0.105)	**1.106*****	(0.288)	**-0.507*****	(0.162)	0.253	(0.328)
Infogames	-0.234	(0.147)	**1.016*****	(0.327)	**-0.690*****	(0.196)	-0.020	(0.345)
Konami	**-0.387*****	(0.122)	0.446	(0.344)	-0.042	(0.179)	0.144	(0.412)
Activision	**-0.280****	(0.111)	**0.693****	(0.291)	-0.020	(0.201)	0.146	(0.445)
Midway	0.039	(0.124)	**1.665*****	(0.345)	-0.281	(0.221)	0.115	(0.423)
Eidos Interactive	**-0.791*****	(0.123)	**1.434*****	(0.308)	**-0.697*****	(0.187)	-0.248	(0.522)
THQ	**-0.320****	(0.157)	**1.621*****	(0.414)	**-0.693***	(0.336)	0.338	(0.529)
Capcom	-0.109	(0.128)	0.657	(0.410)	-0.108	(0.199)	0.356	(0.416)
Namco	0.218	(0.159)	**2.109*****	(0.457)	**0.416****	(0.206)	-0.648	(0.965)
Agetec	-0.132	(0.183)	**2.147*****	(0.429)	**-4.106*****	(1.190)	**-5.610*****	(1.620)
Interplay	**-0.758*****	(0.130)	**1.470*****	(0.310)	**-1.798*****	(0.423)	-1.436	(1.074)
Hasbro	-0.097	(0.150)	**0.941****	(0.392)	-1.016	(0.970)	0.910	(1.626)
2nd Publishers	**-0.461*****	(0.099)	**1.335*****	(0.254)	**-0.388****	(0.182)	0.154	(0.488)
3rd Publishers	**-0.299*****	(0.096)	**0.942*****	(0.269)	**-0.636*****	(0.142)	0.066	(0.336)
4th Publishers	**-0.399*****	(0.109)	**1.334*****	(0.267)	**-0.386****	(0.176)	0.410	(0.382)
Season								
Feb	-0.183	(0.150)	-0.561	(0.429)	0.014	(0.235)	-0.364	(0.767)
Mar	-0.111	(0.140)	-0.564	(0.389)	-0.125	(0.223)	-0.403	(0.627)
Apr	-0.056	(0.162)	-0.218	(0.452)	-0.421	(0.267)	-0.514	(0.810)
May	-0.142	(0.154)	-0.549	(0.456)	-0.199	(0.247)	0.110	(0.701)
Jun	0.050	(0.154)	**-0.947****	(0.443)	-0.259	(0.253)	-1.087	(0.718)
Jul	-0.224	(0.173)	-0.354	(0.530)	-0.249	(0.265)	-1.023	(0.907)
Aug	0.045	(0.153)	-0.474	(0.397)	-0.154	(0.276)	-0.550	(0.741)
Sep	-0.014	(0.130)	-0.469	(0.387)	0.023	(0.213)	-0.215	(0.673)
Oct	-0.129	(0.137)	-0.402	(0.393)	-0.042	(0.211)	-0.358	(0.677)
Nov	-0.109	(0.128)	-0.393	(0.373)	0.054	(0.194)	-0.309	(0.678)
Dec	-0.229*	(0.140)	-0.420	(0.421)	-0.287	(0.231)	-0.198	(0.789)
Other covariates								
Launch Price	**0.018*****	(0.005)	0.003	(0.012)	**0.048*****	(0.007)	-0.025	(0.019)
Time to Console Launch	-0.005	(0.004)	-0.002	(0.009)	**-0.021*****	(0.006)	**0.027****	(0.011)

Notes: Posterior standard deviation between parentheses. *,**,*** indicate zero is not contained in the 90, 95 and 99% highest posterior density region

Table 2: Estimation Results Part I

	Mixture (3) D(t)=Cumulative Sales						All Mixtures	
	Sales Threshold $log(\lambda_i)$		Landing Speed $log(\nu_i)$		Landing Price κ_i		Starting Price ρ_i	
Intercept	2.579	(1.810)	**4.133*** **	(1.363)	**17.34*** **	(1.510)	**40.79*** **	(2.046)
Game Type								
Action	-0.431	(1.179)	0.161	(0.829)	0.751	(0.987)	-1.793	(1.297)
Arcade	-1.171	(1.567)	-1.866	(1.145)	0.543	(1.492)	**-5.244*** **	(1.969)
Children	-1.696	(1.887)	0.551	(1.245)	-1.128	(1.456)	**-10.46*** **	(2.092)
Driving	0.342	(1.203)	1.040	(0.718)	-0.243	(1.007)	-1.363	(1.299)
Family	0.705	(1.641)	-0.012	(1.243)	-1.111	(1.225)	**-5.322*** **	(1.627)
Fighting	-1.416	(1.129)	-0.974	(0.814)	**2.061***	(1.109)	0.378	(1.443)
Role playing	2.021	(1.730)	0.067	(1.356)	**3.162*** **	(1.180)	1.033	(1.460)
Shooter	-0.823	(1.230)	0.170	(0.901)	-0.310	(1.056)	2.050	(1.372)
Sports	-1.147	(1.301)	**-1.369***	(0.845)	-0.987	(0.983)	-1.450	(1.301)
Strategy	-1.545	(1.640)	-0.462	(1.271)	2.364*	(1.240)	1.290	(1.592)
Compilations	-0.603	(1.732)	**2.599** **	(1.185)	**-7.490*** **	(1.534)	**8.880*** **	(3.272)
Publisher								
Electronic Arts	**3.395*** **	(0.647)	**2.077*** **	(0.442)	**1.135***	(0.671)	**1.712** **	(0.807)
Acclaim	0.904	(0.782)	0.039	(0.619)	**-1.572***	(0.865)	1.617	(1.124)
Infogames	0.049	(0.664)	0.119	(0.577)	**-1.766** **	(0.888)	1.262	(1.289)
Konami	**2.240** **	(1.090)	-0.037	(0.656)	**2.535*** **	(0.979)	0.586	(1.199)
Activision	**2.886** **	(1.078)	**1.683*** **	(0.651)	-1.105	(0.962)	-0.439	(1.196)
Midway	1.346	(1.018)	-0.030	(0.875)	-1.617	(1.054)	2.344*	(1.339)
Eidos Interactive	1.674	(1.142)	**1.537*** **	(0.747)	**-2.009** **	(1.013)	**5.029*** **	(1.421)
THQ	**5.719*** **	(1.126)	**2.341*** **	(0.888)	-0.919	(1.172)	2.005	(1.656)
Capcom	2.154	(1.326)	**2.476*** **	(0.869)	1.540	(1.070)	-0.874	(1.324)
Namco	-2.462	(4.770)	-2.518	(2.743)	1.433	(1.554)	2.235	(1.597)
Agetec	0.806	(1.182)	-0.472	(0.714)	**-3.267** **	(1.427)	3.487	(2.106)
Interplay	1.134	(1.241)	**2.043*** **	(0.814)	-0.778	(1.127)	**9.382*** **	(1.741)
Hasbro	0.816	(1.009)	-1.433	(1.460)	**-3.545*** **	(1.289)	**-4.731*** **	(1.720)
2nd Publishers	0.398	(0.933)	-0.035	(0.909)	**-3.134*** **	(0.767)	**1.892***	(1.081)
3rd Publishers	-0.212	(0.597)	0.007	(0.454)	-1.124	(0.702)	**1.947** **	(0.943)
4th Publishers	1.356*	(0.779)	0.408	(0.567)	**-3.216*** **	(0.815)	0.771	(1.212)
Season								
Feb	-1.274	(2.237)	-0.508	(1.474)	-0.121	(1.254)	-2.178	(1.747)
Mar	0.364	(1.099)	-0.344	(0.890)	**2.038***	(1.123)	**-2.663***	(1.559)
Apr	**-10.56*** **	(3.330)	**-8.255*** **	(2.689)	**2.306***	(1.375)	0.148	(1.878)
May	**-12.00*** **	(2.095)	**-8.820*** **	(1.870)	1.499	(1.281)	-1.118	(1.811)
Jun	**-11.45*** **	(2.627)	**-8.422*** **	(1.864)	**3.648*** **	(1.230)	**-3.058***	(1.717)
Jul	**-3.430** **	(1.819)	**-3.950*** **	(1.306)	1.227	(1.367)	-1.847	(1.926)
Aug	1.129	(1.519)	0.173	(1.202)	0.236	(1.235)	**-3.719** **	(1.655)
Sep	0.739	(0.877)	0.840	(0.709)	1.397	(1.088)	-2.537	(1.536)
Oct	0.849	(0.892)	0.652	(0.761)	1.112	(1.124)	-0.832	(1.573)
Nov	0.588	(0.990)	0.597	(0.720)	0.617	(1.073)	-0.965	(1.498)
Dec	0.109	(0.982)	0.358	(0.766)	**2.150***	(1.173)	0.534	(1.682)
Launch Info								
Launch Price	**0.155*** **	(0.018)	**0.068*** **	(0.015)	–	–	–	–
Time to Console Launch	**-0.122*** **	(0.025)	**-0.059*** **	(0.018)	**0.127*** **	(0.025)	**0.401*** **	(0.033)

Notes: Posterior standard deviation between parentheses. *,**,*** indicate zero is not contained in the 90, 95 and 99% highest posterior density region

Table 3: Estimation Results Part II

	Latent Utility of Sales Mixture		Latent Utility of Time Mixture	
Intercept	3.727***	(0.579)	0.549	(0.445)
Game Type				
Action	0.699*	(0.360)	0.260	(0.269)
Arcade	-0.032	(0.543)	0.404	(0.451)
Children	0.481	(0.479)	0.005	(0.456)
Driving	0.708*	(0.402)	0.288	(0.278)
Family	-0.100	(0.451)	-0.577*	(0.333)
Fighting	1.153***	(0.427)	0.357	(0.372)
Role playing	-0.304	(0.552)	-0.146	(0.355)
Shooter	0.809	(0.567)	0.716**	(0.297)
Sports	-0.010	(0.372)	0.057	(0.252)
Strategy	0.342	(0.613)	-0.055	(0.362)
Compilations	0.930*	(0.530)	-0.258	(0.438)
Publisher				
Electronic Arts	-0.689	(0.514)	-0.137	(0.239)
Acclaim	-0.723	(0.583)	-0.365	(0.284)
Infogames	0.723	(0.456)	-0.332	(0.360)
Konami	1.110**	(0.469)	0.068	(0.343)
Activision	1.060**	(0.450)	0.356	(0.325)
Midway	0.884*	(0.454)	-0.119	(0.384)
Eidos Interactive	0.002	(0.668)	0.265	(0.365)
THQ	-0.287	(0.531)	-0.017	(0.459)
Capcom	-0.355	(0.451)	-0.821**	(0.357)
Namco	-0.043	(0.649)	-0.503	(0.426)
Agetec	0.592	(0.558)	0.592	(0.512)
Interplay	0.648	(0.626)	0.800*	(0.430)
Hasbro	-0.364	(0.512)	0.303	(0.380)
2nd Publishers	0.203	(0.427)	0.387	(0.305)
3rd Publishers	0.324	(0.402)	-0.025	(0.272)
4th Publishers	0.510	(0.374)	0.164	(0.301)
Season				
Feb	0.159	(0.467)	-0.026	(0.361)
Mar	0.002	(0.454)	0.441	(0.297)
Apr	0.448	(0.575)	0.296	(0.431)
May	-0.309	(0.499)	-0.361	(0.344)
Jun	0.067	(0.533)	0.709**	(0.381)
Jul	0.149	(0.547)	0.007	(0.417)
Aug	-0.197	(0.479)	0.355	(0.367)
Sep	0.008	(0.373)	-0.214	(0.259)
Oct	0.156	(0.410)	0.285	(0.293)
Nov	0.070	(0.357)	0.069	(0.243)
Dec	0.666	(0.418)	0.329	(0.307)
Launch Info				
Launch Price	-0.162***	(0.013)	0.004	(0.007)
Time to Launch	0.010	(0.015)	-0.012	(0.008)

Notes: Posterior standard deviation in parentheses. *,**,*** indicate zero is not contained in the 90, 95, and 99% highest posterior density region.

Table 4: Results of Hierarchical Structure for Mixture Probabilities

Game Title	Forecasted Months	St. Dev. Price	Forecast RMSE	Forecast RMSE AR(1)	Log of Predicted Density	Log Likelihood of predicted AR (1)
NHL 2001	10	0.18	0.17	0.15	-0.89*	-3.47
JJ'S VR FOOTBALL 98	8	2.39	1.76*	5.19	-5.06*	-6.79
HIGH HEAT BSBALL 2002	18	7.14	2.18*	11.92	-10.25*	-142.23
MADDEN NFL 98	12	4.56	2.55*	5.03	-11.05*	-27.81
MR DOMINO	18	8.33	3.10*	12.34	-17.22*	-188.45
THE CROW CITY ANGELS	18	14.53	3.24*	26.27	-12.15*	-369.19
PITBALL	18	13.49	3.72*	27.92	-12.50*	-264.59
FROGGER 2	18	10.48	3.86*	22.53	-12.30*	-2421.81
BIG OL' BASS 2	18	14.45	3.92*	22.63	-15.22*	-485.79
MK & ASHLEY WINNER'S	18	11.88	4.11*	17.46	-11.90*	-493.25
CIVILIZATION 2	18	9.73	4.25*	12.52	-8.94*	-1009.23
PONG	18	11.43	4.37*	20.81	-14.54*	-646.32
ROGUE TRIP	14	1.80	4.38	1.90	-16.24	-0.58
RESIDENT EVIL 3:NEMES	18	10.16	4.70*	10.34	-15.91*	-71.64
ETERNAL EYES	18	8.31	4.92*	9.45	-24.18*	-82.53
TEKKEN 2	18	7.39	5.13*	8.54	-15.13*	-85.26
TEST DRIVE 4	18	11.50	5.39*	28.29	-12.53*	-511.42
F1 WRLD GRAND PRIX 00	18	7.11	5.63*	7.52	-29.76*	-50.37
FADE TO BLACK	18	9.09	5.88*	8.58	-21.99*	-38.53
SHEEP RAIDER	18	9.35	6.03*	11.20	-81.57*	-112.25
G POLICE2:WPN JUSTICE	9	10.79	6.04*	24.87	-8.60*	-386.84
RISK	10	9.50	6.55*	12.39	-13.02*	-267.31
SYNDICATE WARS	18	8.93	6.66*	12.83	-16.71*	-55.53
JUGGERNAUT	18	9.33	6.71*	16.33	-51.62*	-60.97
KISS PINBALL	10	8.47	6.73*	13.79	-11.21*	-128.41
BACKYARD SOCCER	18	16.59	6.74*	23.35	-24.94*	-652.10
OLYMPIC SUMMER GAMES	18	8.57	7.02*	12.52	-16.79*	-38.77
NECTARIS:MILITARY MAD	18	13.34	7.06*	19.63	-16.75*	-292.34
T.CLANCYS ROGUE SPEAR	18	5.38	7.88	4.54	-21.11	-16.62
TOCA 2 CAR CHALLENGE	18	13.75	7.97*	13.93	-23.36*	-177.86
NFL XTREME 2	18	14.35	8.27*	24.53	-20.69*	-467.21
ARENA FOOTBALL	17	3.40	8.35	4.08	-14.76*	-23.53
FINAL FANTASY IX	13	6.23	8.43*	12.81	-10.78*	-32.38
SHEEP	18	3.47	8.83	3.54	-22.08	-4.11
SIMPSON'S WRESTLING	12	8.66	8.87*	12.12	-16.69*	-31.70
POCKET FIGHTER	18	10.51	9.02*	17.25	-17.09*	-169.35
POWERBOAT RACING	18	10.50	9.19*	24.08	-14.13*	-466.81
GRAND SLAM 97	18	11.09	9.53*	11.69	-24.66*	-121.27
RAMPAGE WORLD TOUR	6	2.88	9.67	4.58	-1245.7	-6.05
EAGLE ONE: HARRIER	13	11.43	10.5*	13.02	-50.33*	-847.83
STRIKER PRO 2000	9	10.66	10.6*	20.87	-10.52*	-139.91
NEWMAN/HAAS RACING	16	3.88	11.31	4.63	-38.44	-4.55
DISCWRLD 2:MRTLY BYTE	18	6.31	11.42	5.95	-87.15*	-41.79
CROSSROAD CRISIS	18	9.77	12.4*	15.33	-93.93*	-458.48
SLAM N JAM 96	18	10.23	13.3*	19.53	-18.82*	-280.41
NBA LIVE 2002	18	9.23	14.4*	21.76	-80.22*	-466.39
ARMD COR 2 PRJ PNTSMA	15	8.71	15.0*	16.21	-11.77*	-263.19
CRASH TEAM RACING	18	15.92	15.8*	17.91	-342.07	-117.05
DISNEY'S DINOSAUR	18	5.00	16.35	5.68	-27.82	-15.57
NFL BLITZ 2000	18	5.63	17.57	6.41	-30.46*	-130.64

Notes: * Means the RMSE or the predictive likelihood is smaller in our model than in the AR(1)

Table 5: Forecasting Performance

Game Title	Forecast Horizon	St.Dev. Price[a]	Log of Predictive Density (LPD) Original Model	Log of Predicted Density (LDP) Alt. Model
NHL 2001	10	0.18	-0.89 *	-0.90
JJ'S VR FOOTBALL 98	8	2.39	-5.06 *	-4.89
HIGH HEAT BSBALL 2002	18	7.14	-10.25 *	-9.92
MADDEN NFL 98	12	4.56	-11.05 *	-11.12
MR DOMINO	18	8.33	-17.22	-15.86
THE CROW CITY ANGELS	18	14.53	-12.15 *	-11.29
PITBALL	18	13.49	-12.50 *	-12.06
FROGGER 2	18	10.48	-12.30 *	-12.51
BIG OL' BASS 2	18	14.45	-15.22 **	-16.29
MK & ASHLEY WINNER'S	18	11.88	-11.90 *	-12.11
CIVILIZATION 2	18	9.73	-8.94 **	-11.36
PONG	18	11.43	-14.54	-13.10
ROGUE TRIP	14	1.80	-16.24 **	-30.14
RESIDENT EVIL 3:NEMES	18	10.16	-15.91 **	-17.48
ETERNAL EYES	18	8.31	-24.18 **	-25.35
TEKKEN 2	18	7.39	-15.13 **	-16.17
TEST DRIVE 4	18	11.50	-12.53 *	-12.40
F1 WRLD GRAND PRIX 00	18	7.11	-29.76	-26.22
FADE TO BLACK	18	9.09	-21.99 **	-23.64
SHEEP RAIDER	18	9.35	-81.57 **	-121.60
G POLICE2:WPN JUSTICE	9	10.79	-8.60 *	-8.56
RISK	10	9.50	-13.02 **	-33.94
SYNDICATE WARS	18	8.93	-16.71	-13.63
JUGGERNAUT	18	9.33	-51.62 **	-98.83
KISS PINBALL	10	8.47	-11.21 *	-11.05
BACKYARD SOCCER	18	16.59	-24.94	-21.56
OLYMPIC SUMMER GAMES	18	8.57	-16.79	-14.71
NECTARIS:MILITARY MAD	18	13.34	-16.75 *	-16.17
T.CLANCYS ROGUE SPEAR	18	5.38	-21.11 **	-22.90
TOCA 2 CAR CHALLENGE	18	13.75	-23.36 **	-26.08
NFL XTREME 2	18	14.35	-20.69	-17.40
ARENA FOOTBALL	17	3.40	-14.76 *	-14.56
FINAL FANTASY IX	13	6.23	-10.78	-9.54
SHEEP	18	3.47	-22.08 **	-23.30
SIMPSON'S WRESTLING	12	8.66	-16.69 *	-16.84
POCKET FIGHTER	18	10.51	-17.09 *	-16.58
POWERBOAT RACING	18	10.50	-14.13 *	-14.76
GRAND SLAM 97	18	11.09	-24.66 *	-23.81
RAMPAGE WORLD TOUR	6	2.88	-1245.7 **	-2072.64
EAGLE ONE: HARRIER	13	11.43	-50.32 **	-77.20
STRIKER PRO 2000	9	10.66	-10.52 *	-11.26
NEWMAN/HAAS RACING	16	3.88	-38.44 **	-54.93
DISCWRLD 2:MRTLY BYTE	18	6.31	-87.15	-38.19
CROSSROAD CRISIS	18	9.77	-93.93	-34.08
SLAM N JAM 96	18	10.23	-18.82	-15.18
NBA LIVE 2002	18	9.23	-80.22 **	-82.06
ARMD COR 2 PRJ PNTSMA	15	8.71	-11.77 **	-14.41
CRASH TEAM RACING	18	15.92	-342.07 **	-397.18
DISNEY'S DINOSAUR	18	5.00	-27.82	-18.46
NFL BLITZ 2000	18	5.63	-30.46 **	-34.48

Notes:** means that the Original Model LPD is greater than the Alternative LPD by more than 1 unit, * means that the difference between the original and alternative are less than 1 unit. Alt. stand for Alternative and St.Dev for Standard Deviation.

Table 6: Comparison with Alternative Model

A Estimation Methodology

To draw inference on the parameters we will rely on a Bayesian analysis and more specifically the Gibbs sampler. Whenever possible we use Gibbs sampling with block updating and when there are no closed form sampling distributions we rely on the Metropolis algorithm. We run a Markov Chain for 200 thousand iterations of which the first 100 thousand are discarded for burn-in and we keep each tenth remaining draws. This Markov Chain has the posterior distribution of the parameters and the latent trigger variable indicators S_i $i = 1, \ldots, N$ as the stationary distribution. We programmed all our routines in Ox (see Doornik (2007)) and our graphs in R (see R Development Core Team (2005)).

In all what follows we collect the first level model parameters in the blocks: $\tau_i = (\rho_i, \kappa_i, \alpha_i,\ \sigma_i, \lambda_k, \nu_k)$, $\rho = (\rho_1, ..., \rho_N)$, $\kappa = (\kappa_1, ..., \kappa_N)$, $\alpha = (\alpha_1, ..., \alpha_N)$, $\sigma^2 = (\sigma_1^2, ..., \sigma_N^2)$, $\lambda_k = (\ln(\lambda_{ki}), . .., \ln(\lambda_{kN}))$ and finally $\nu_k = (\ln(\nu_{ik}), ..., \ln(\nu_{Nk}))$.

We further collect all hyper-parameters in the following blocks: $\theta = (\gamma^P, \gamma^L, \Pi, \mathbf{\Omega})$, where $\mathbf{\Omega} = (\mathbf{\Omega_1}, ..., \mathbf{\Omega_K})$, $\Pi = (\pi_1, ..., \pi_K)$. We have that $\gamma^P = (\gamma^\kappa, \gamma^\rho)$ where $\gamma^\kappa = (\gamma_1^\kappa, ..., \gamma_M^\kappa)$ and $\gamma^\rho = (\gamma_1^\rho, ..., \gamma_M^\rho)$. Finally, $\gamma^L = (\gamma_1^L, \ldots, \gamma_K^L)$ where $\gamma_k^L = (\gamma_k^\lambda, \gamma_k^\nu)$ and $\gamma_k^\lambda = (\gamma_{k1}^\lambda, ..., \gamma_{kM}^\lambda)$ and $\gamma_k^\nu = (\gamma_{k1}^\nu, ..., \gamma_{kM}^\nu)$. M refers to the number of variables in Z, K refers to the number of mixtures (same as number of triggers), and N refers to the total number of products. Next $\mathbf{Z}=(Z_1, ..., Z_M)$ and $\phi(x; \mu, \sigma^2)$ denotes the normal pdf distribution with mean μ and variance σ^2 evaluated at x. Finally, $p()$ denotes a general density function and $IW(\widehat{\Omega}, N)$ denotes the inverted Whishart distribution with scale matrix $\widehat{\Omega}$ and N degrees of freedom.

Note that in this context we treat the product specific *parameters* τ_i as latent variables. We consider the log of λ_{ki} and ν_{ki} $k = 1, ...K$, $i = 1, \ldots, N$ as focal parameters strictly for convenience and to impose that λ_{ki} and ν_{ki} are positive. This has no impact on the results. In this Markov Chain we will sample the latent variables alongside the parameters.

The complete data likelihood for product i is

$$p(\mathbf{P}_i, S_i, \tau_i | \theta) = \pi_{S_i} \times p(\mathbf{P}_i | S_i, \tau_i, \theta) \times p(\tau_i | \theta), \tag{12}$$

where $\mathbf{P}_i = (P_i(0), ..., P_i(T))$ and $p(\mathbf{P}_i|S_i, \tau_i, \theta)$ is equal to

$$p(P_i(0)|S_i, \tau_i, \theta) \times \prod_{t=1}^{t=T} p(P_i(t)|P_i(t-1), S_i, \tau_i, \theta). \tag{13}$$

Furthermore, we have that the first observation likelihood is

$$p(P_i(0)|S_i, \tau_i, \theta) = \phi\left(P_i(0); P_i^*(0), \frac{1}{1-\alpha^2}\sigma_i^2\right), \tag{14}$$

and all other observations have as likelihood

$$p(P_i(t)|P_i(t-1), S_i, \tau_i, \theta) = \phi\left(P_i(t); P_i^*(t) + \alpha_i[P_i(t-1) - P_i^*(t-1)], \sigma_i^2\right). \tag{15}$$

Next, we have

$$p(\tau_i|\theta) = p(\rho_i, \kappa_i|\theta) \prod_{k=1}^{K} p(\lambda_{ki}, \nu_{ki}|\theta), \tag{16}$$

where

$$p\left((\rho_i, \kappa_i)|\theta\right) = \phi\left((\rho_i, \kappa_i)'; \gamma^{P\prime} Z_i, \mathbf{\Sigma}\right), \tag{17}$$

and

$$p\left((\lambda_{ki}, \nu_{ki})|\theta\right) = \phi\left((\lambda_{ki}, \nu_{ki})'; \gamma_k^{L\prime} Z_i, \mathbf{\Omega}_k\right). \tag{18}$$

We impose flat priors on all almost all parameters, for α_i we set a uniform prior on the interval (-1,1) to impose stationarity. This completes the main model specification and next we discuss how we sample from the posterior distribution for all parameters.

Sampling distributions

If π_k is fixed across products, the density of S_i conditional on $\mathbf{P_i}$, τ_i, and θ equals a Multinomial distribution with probabilities proportional to

$$\pi_{S_i} \times p(\mathbf{P}_i|S_i, \tau_i, \theta). \tag{19}$$

The full conditional distribution for α_i is a truncated normal on the interval [-1,1], where the mean and variance are given by applying the Ordinary Least Squares formulas to a regression of $P_i(t)$-$P_i^*(t)$ on its lag with known variance of the disturbance term σ_i^2. A draw for σ_i^2 can be obtained using the Metropolis-Hastings sampler and taking as candidate

$$\sigma^2_{i_{cand}} = \frac{\sum_{t=1}^{T}(\hat{\varepsilon}_i(t))^2}{w} \quad \text{where} \quad w \sim \chi^2_{(T-1)}, \tag{20}$$

where $\hat{\varepsilon}_i(t)$ is the residual of equation (4) given all other parameters. We evaluate this candidate and the current draw of σ_i^2 in the conditional distribution of the first observation given in equation (14). Hence we take the candidate as the next drawn value of σ_i^2 with probability

$$\min\left(1, \frac{\phi\left(P_i(0); P_i^*(0), \frac{1}{1-\alpha^2}\sigma^2_{i_{cand}}\right)}{\phi\left(P_i(0); P_i^*(0), \frac{1}{1-\alpha^2}\sigma^2_{i_{current}}\right)}\right). \tag{21}$$

To derive the full conditional distribution of κ_i and ρ_i we first rewrite equations (4) and (5) as

$$\sqrt{1-\alpha_i^2}P_i(0) = [\sqrt{1-\alpha_i^2}h_{S_i}(0)] \times \kappa_i + [\sqrt{1-\alpha_i^2}h_{S_i}(0)] \times \rho_i + \varepsilon_i(0), \tag{22}$$

and

$$P_i(t) - \alpha_i P_i(t-1) = [1 - h_{S_i}(t) - \alpha_i(1 - h_{S_i}(t))] \times \kappa_i + [h_{S_i}(t) - \alpha_i h_{S_i}(t)] \times \rho_i + \varepsilon_i(t). \tag{23}$$

These equations should be combined with the specification of the hierarchical layer in (7) as follows:

$$\begin{pmatrix} Y_i \\ \gamma^{\rho'} Z_i \\ \gamma^{\kappa'} Z_i \end{pmatrix} = \begin{pmatrix} X_i^A & X_i^B \\ 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \rho_i \\ \kappa_i \end{pmatrix} + \begin{pmatrix} \varepsilon_i \\ \omega^\rho \\ \omega^\kappa \end{pmatrix}, \tag{24}$$

where we define X_i^A and X_i^B as

$$X_i^A = \begin{pmatrix} \sqrt{1-\alpha_i^2}(1-h_{S_i}(0)) \\ 1-h_{S_i}(1)-\alpha_i(1-h_{S_i}(1)) \\ \vdots \\ 1-h_{S_i}(T_i)-\alpha_i(1-h_{S_i}(T_i)) \end{pmatrix} \quad \text{and} \quad X_i^B = \begin{pmatrix} \sqrt{1-\alpha_i^2}h_{S_i}(0) \\ h_{S_i}(1)-\alpha_i h_{S_i}(1) \\ \vdots \\ h_{S_i}(T_i)-\alpha_i h_{S_i}(T_i) \end{pmatrix}, \tag{25}$$

and Y_i as

$$Y_i = \begin{pmatrix} \sqrt{1-\alpha_i^2}P_i(0) \\ P_i(1)-P_i(0) \\ \vdots \\ P_i(T)-P_i(T-1) \end{pmatrix}. \tag{26}$$

Finally, we can draw κ_i and ρ_i from

$$N\left((W_i'\Gamma_i^{-1}W_i)^{-1}W_i'\Gamma_i^{-1}Y_i, (W_i'\Gamma^{-1}W_i)^{-1}\right), \tag{27}$$

where

$$W_i = \begin{pmatrix} X_i^A & X_i^B \\ 1 & 0 \\ 0 & 1 \end{pmatrix} \quad \text{and} \quad E\left(\begin{pmatrix} \varepsilon_i & \omega^\rho & \omega^\kappa \end{pmatrix}\begin{pmatrix} \varepsilon_i \\ \omega^\rho \\ \omega^\kappa \end{pmatrix}\right) = \begin{pmatrix} \sigma_i^2 I & 0 \\ 0 & \mathbf{\Sigma} \end{pmatrix} = \Gamma_i. \tag{28}$$

Due to the non-linearity in the price patterns, the conditional distributions of λ_k and ν_k are not of a known form. We will sample each parameter one at a time using a random walk Metropolis Hastings sampler. Given the current draw of one of these parameters we draw a candidate by adding a draw from a normal with mean zero and a fixed variance. This candidate draw for λ_k and ν_k is accepted with probability

$$\min\left(1, \frac{p(\lambda_{ki}^{cand}|\nu_{ki})}{p(\lambda_{ki}^{current}|\nu_{ki})}\right) \quad \text{and} \quad \min\left(1, \frac{p(\nu_{ki}^{cand}|\lambda_{ki})}{p(\nu_{ki}^{current}|\lambda_{ki})}\right), \tag{29}$$

respectively. The posterior of the $i'th$ element of λ_k is

$$p(\lambda_{ki}|\nu_{ki}) = p(P_i(0)|S_i, \tau_i, \theta) \prod_{t=1}^{t=T} p(P_i(t)|P_i(t-1)S_i, \tau_i, \theta)\phi\left(\lambda_{ki}; \lambda_{ki}|\nu_{ki}, \Omega_k^{\lambda_{ki}|\nu_{ki}}\right), \quad (30)$$

and the posterior of the $i'th$ element of ν_k is

$$p(\nu_{ki}|\lambda_{ki}) = p(P_i(0)|S_i, \tau_i, \theta) \prod_{t=1}^{t=T} p(P_i(t)|P_i(t-1)S_i, \tau_i, \theta)\phi\left(\nu_{ki}; \nu_{ki}|\lambda_{ki}, \Omega_k^{\nu_{ki}|\lambda_{ki}}\right). \quad (31)$$

Here $x|y$ refers to the conditional mean of x given y and $\sigma^{x|y}$ refers to the conditional variance of x given y. These are conditional posterior distributions because we allow λ_k and ν_k to be correlated to each other. In other words, the timing of the price cut and the speed of the price cut might be correlated and these correlation is different across mixtures. The variance of the proposal density is chosen such that we obtain an acceptance rate close to approximately 25%, that is the optimal rate for high-dimensional models (see Robert and Casella (2004, page 316), Carlin and Louis (2000, page 154) or Gamerman and Lopes (2006, page 196)).

The conditional distribution of $\pi_1, \ldots, \pi_K$ is a Dirichlet distribution with parameters $1 + \sum_i 1[S_i = 1], \ldots, 1 + \sum_i 1[S_i = K]$; that is, we draw each π_k proportional to the number of products assigned to mixture k, that is $\sum_1 1[S_i = k]$, and naturally restrict $\sum_k \pi_k = 1$.

Given the latent variables in τ_i sampling the hyper-parameters of the hierarchical part for the marginal costs, launch price, and price landing characteristics is relatively straightforward. We draw γ^P from a normal

$$\gamma^P \sim N\left(\begin{array}{c} (\mathbf{Z}'\mathbf{Z})^{-1} Z'\kappa \\ (Z'\mathbf{Z})^{-1}\mathbf{Z}'\rho \end{array}, \boldsymbol{\Sigma} \otimes (\mathbf{Z}'\mathbf{Z})^{-1}\right), \quad (32)$$

and $\gamma_k^L|\Omega_k$ from

$$N\left(\begin{array}{c}\frac{1}{1+g}(\mathbf{Z'Z})^{-1}\mathbf{Z'}\lambda_{ki}\\ \frac{1}{1+g}(\mathbf{Z'Z})^{-1}\mathbf{Z'}\nu_{ki}\end{array}, \frac{1}{1+g}\mathbf{\Omega}_k \otimes (\mathbf{Z'Z})^{-1}\right). \tag{33}$$

The factor g comes from the g-prior which states that the variance of (λ_{ki}, ν_{ki}) is proportional to the variance of the data. See Fernandez et al. (2001) for a detailed discussion.

Finally, we draw $\mathbf{\Sigma} \sim IW\left(\widehat{\mathbf{\Sigma}}, N\right)$ where

$$\widehat{\mathbf{\Sigma}} = \begin{pmatrix} \widehat{\omega}^{\kappa} \\ \widehat{\omega}^{\rho} \end{pmatrix} (\widehat{\omega}^{\kappa}, \widehat{\omega}^{\rho}) \tag{34}$$

and $\widehat{\omega}_i^{\kappa} = \kappa_i - Z_i'\gamma^{\kappa}$, $\widehat{\omega}_i^{\rho} = \rho_i - Z_i'\gamma^{\rho}$ and $\widehat{\omega}^{\kappa} = (\widehat{\omega}_1^{\kappa} \ldots \widehat{\omega}_N^{\kappa})$ and $\widehat{\omega}^{\rho} = (\widehat{\omega}_1^{\rho} \ldots \widehat{\omega}_N^{\rho})$. Next, we draw $\mathbf{\Omega_k} \sim IW\left(\widehat{\mathbf{\Omega}}_\mathbf{k} + \mathbf{G} + I_2, 7 + N\right)$ where

$$\widehat{\mathbf{\Omega}}_\mathbf{k} = \begin{pmatrix} \widehat{\eta}_k^{\lambda} \\ \widehat{\eta}_k^{\nu} \end{pmatrix} (\widehat{\eta}_k^{\lambda}, \widehat{\eta}_k^{\nu}), \tag{35}$$

and $\widehat{\eta}_k^{\lambda} = \log(\lambda_k) - Z'\gamma_k^{\lambda}$ and $\widehat{\eta}_k^{\nu} = log(\nu_k) - Z'\gamma_k^{\nu}$. finally $\mathbf{G}_k$ is defined as

$$\widehat{\mathbf{G}}_k = \begin{pmatrix} \widehat{\gamma}_k^{\lambda} \\ \widehat{\gamma}_k^{\nu} \end{pmatrix} g(\mathbf{Z'Z})^{-1}(\widehat{\gamma}_k^{\lambda}, \widehat{\gamma}_k^{\nu}) \tag{36}$$

and I_2 is an identity matrix size 2×2.

Hierarchical Structure in the Mixture Probabilities

The previous steps give the methodology to analyze our model without a hierarchical specification on the mixture probabilities π_k. As discussed in this article, the model can be easily expanded to include a hierarchical specification on the mixture probabilities. As before, we will assume that π_{ki} differs across products but here we test if a multinomial probit specification that depends on $\mathbf{Z}$ is useful to explain their heterogeneity. For that we need to define first K latent variables for each product i

$$y^*_{ki} \sim N(Z_i'\delta_k, 1) \tag{37}$$

where $\delta_1 = 0$ for identification. Product i belongs to mixture m if y^*_{mi} is the largest of all y^*_{ki} $k = 1, \ldots, K$. Given (37) , we can write the conditional distribution of y^*_{mi} given the other latent utilities (-m), denoted as $y^*_{-m,i}$, as follows:

$$\begin{aligned} p(y^*_{mi}|y^*_{-m,i}, \theta, \tau_i, S_i) = \quad & p(y^*_{mi} > \max(y^*_{-m,i})) \times p(\mathbf{P}_i, S_i = m, \tau_i|\theta) \\ & + p(y^*_{mi} < \max(y^*_{-m,i})) \times p(\mathbf{P}_i, S_i = m^*, \tau_i|\theta) \end{aligned} \tag{38}$$

where $m^* = \underset{m \neq k}{argmax}(y^*_{ki})$. Based on (38) we can apply the inverse cdf technique to draw y^*_{mi} from its full conditional distribution. Note that in this specification the indicator variable S_{ki} is determined based on y^*_{mi} and the δ_m parameters can be obtained from a normal with mean $(Z_i'Z_i)^{-1}Z_i'\delta_k$ and variance $(Z_i'Z_i)^{-1}$ for $m = 2, \ldots, K$.

Posterior Predictive Density

We used two measures to compare predictive performance in Table 5: the root mean squared error and the log of the posterior predictive density for observations after $t = 7$. The predictive density $\log(p(P_i(7)_{,\ldots,}P_i(T)|P_i(1)_{,\ldots,}P_i(6)))$ is defined as:

$$\log \int\int\int p(P_i(7)_{,\ldots,}P_i(T)|P_i(1)_{,\ldots,}P_i(6), S_i, \tau_i, \theta) \times p(S_i, \tau_i, \theta|P_i(1)_{,\ldots,}P_i(6))dS_i d\tau_i d\theta \tag{39}$$

That is, we compute the log of the density for the forecast sample given the six observations included in the model and the posterior of all model parameters given these latter observations. The posterior predictive density can easily be obtained from the MCMC output by taking the log of the average out-of-sample likelihood over all draws.

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