http://dx.doi.org/10.15830/kmr.2015.30.4.21

네트워크 효과가 존재하는 내구재에 대한 소비자의 정보 탐색 및 구매 모형

Modeling Consumer Search and Purchase in Durable Goods Markets with Network Effects

김이진 • Kim, Yijin, 송인성 • Song, Inseong

본 연구에서는 네트워크 효과가 존재하는 내구재 신제품에 대한 소비자들의 웹 정보 탐색 행동과 구매 행동에 대한 구조적 동적 모형을 개발하였다. 이 모형에서는, 소비자들은 웹 탐색을 통해 각 브랜드의 궁극적인 네트워크 크기에 대한 판단을 하게 되며 이러한 판단을 기초로 최적 구매 시점과 구매 브랜드를 결정한다고 가정한다. 이러한 개별 소비자들의 정보 탐색 및 구매 행동을 합산하여 시장 수준의 탐색량과 판매량이 결정되게 된다. 본 모형을 미국의 비디오 게임 콘솔 시장의 제품 판매 자료와 구글트렌드 자료를 이용하여 추정하였고, 추정된 결과를 이용하여 경쟁 브랜드명이 키워드인 검색 광고를 구매하는 전략의 효과를 계량화하는 정책 시뮬레이션을 실행하여 검색 광고 전략과 관련된 새로운 통찰을 이끌어내었다.

핵심주제어: 소비자 탐색, 신제품 구매 의사 결정, 네트워크 효과, 구조적 동적 모형

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ISSN: 1229-456x (print)

ABSTRACT

This study develops a dynamic structural model of consumers' web search and purchase behaviors of a new durable product with network externalities. The model assumes that consumers engage in web search before purchase in order to make judgment on the network size of each brand and determine their optimal purchase timing and brand choice based on such judgment. The model describes market level web searches and purchases as the aggregated outcomes of individual consumer level dynamic utility maximizing behaviors. The model is applied to the U.S. video game console market. Using the online search volume data from Google Trends together with the sales data, we estimate the model with nested fixed point algorithm. The estimation results show that consumers are heterogeneous in terms of intrinsic brand preferences, sensitivity to information from web search, and search cost. In a policy simulation, we quantify the impact of purchasing a competitor's brand name as a keyword for search advertising and draw managerial implications regarding keyword search advertising strategies.

Keywords: Consumer Search, New Product Adoption, Network Effects, Dynamic Structural Models

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Ⅰ. Introduction

Given the high involvement associated with the purchase of durable products, consumers tend to collect information regarding the products in consideration as much as possible. Such information search behaviors should be well demonstrated for the purchase of durable products with network externalities. For markets of durable products with network effects, the utility of consuming a product is highly dependent upon the number of other consumers who adopt the same product. For example, a video game console is more valuable to consumers if more game titles are available for the console type. If a game console brand does not have a variety of game software titles, the brand has little utility of consumption. The availability of complement products for a product type is also a function of the popularity of the product type among consumers because game developers would want to produce game titles for popular product platform. Thus a more popular platform is likely to bring more utility to consumers. This principle does not require the existence of complementary products. For example, a more popular messenger application, such as Kakao Talk, will bring more utility to users as a user is likely to be connected to more people with it.

In fact, the existence of the network externalities posits a challenge to consumers. It is important for an individual consumer to purchase a product that would eventually become a popular type, especially for products that consumer cost for multi-homing is substantial. So consumers who consider purchasing a product would collect information to make judgment on which brands would become popular. Such judgment would be straightforward for consumers who purchase a product in the later periods of the product life cycle as the popular brand is almost known by the time of their purchases, i.e., the cumulative sales and the eventual availability of complement products by that time are very informative. However, in the earlier periods of the product life cycle, the current cumulative sales figure alone may not be as informative in predicting the popular product as in the later periods because the early period market status is still subject to future change. So consumers who consider purchasing a product in earlier periods would look for additional information from other sources. Such consumers are likely to search for information regarding the number of other consumers who are interested in a particular brand. The more consumers are interested in a particular brand, the more the brand is likely to become the market standard. While consumers conventionally have relied on information sources such as word of mouth and advertisements on TV, radio, or newspapers, searching online has become one of the major sources of the information acquisition with the spread of the Internet. A study conducted by GE Capital Retail Bank reported that 81% of consumers research online before making major purchases and that 60% of consumers start their research by visiting a search engine (Retailing Today 2013).

Given the heavy usage of web searching in the consumers' pre-purchase information collection behaviors, it is important to model how consumers search information online and how search behaviors influence their purchase decisions in order to understand consumer behaviors in a market with network effects. This issue is also of a practical interest to marketing managers. Knowledge regarding when consumers start searching for information about the product, how they decide which alternatives to search for, and how they utilize the information in their purchase decisions can provide insights to marketing managers who try to design marketing programs such as search advertising strategies.

Consumers' information search behavior has been an important topic in economics and marketing literature. Since the pioneering work of Stigler (1961), search behavior has been modeled as a choice resulting from weighing the benefit and cost of the search. Based on an economic cost-benefit framework (Stigler 1961; Weitzman 1979), a number of studies in marketing address consumer information search and purchase choice through a structural modeling approach. (see, for example, Mehta, Rajiv, and Srinivasan 2003; Erdem, Keane, Öncü, and Strebel 2005; Kim, Albuquerque, and Bronnenberg 2010) This study also formulates a dynamic structural model to describe consumer search and purchase behavior. Our study contributes to the literature by exploring how web search volume and sales are related. It is also unique in the sense that it describes the market level search volumes and sales volumes as aggregated outcomes of individual consumer level dynamic utility maximization behaviors.

The study proposes a dynamic structural model that jointly explains consumers' web search and purchase behavior in a market for durable products with network effects. In such a market, the utility of each product increases in the number of others using the product as the complement products are likely to be abundant, and consumers form beliefs about the eventual popularity of a product by searching for the relevant information. Since consumers are uncertain about how the installed base of a product will evolve in the early stage of the product introduction, consumers may delay purchase until they have done enough searching and become sure that the size of the installed base has reached an acceptable level. Thus, forward-looking consumers optimize purchase timing by the trade-off between early purchase with large uncertainty in the prediction of the eventual installed base and late purchase with less uncertainty through additional web search. The model is applied to the U.S. video game console industry using the online search volume data from Google Trends and the sales data. We account for consumer heterogeneity by a latent class specification and find three consumer segments that are heterogeneous in terms of intrinsic preferences for each brand, sensitivity to information from web search, and search cost. This model allows us to quantify the impact of purchasing a competitor's brand name as a keyword for search advertising. Keyword search advertising is a form of online advertising that displays advertisements on a search result webpage when specific keywords are typed in a search engine. Annual revenues of the Internet advertising industry show strong growth, and search advertising stands out as the dominant form of online advertising (Interactive Advertising Bureau 2015). For this reason, the impact of keyword search advertising has become an interesting topic. We specifically focus on the impact of purchasing a competitor's brand name as a keyword for search advertising, and investigate this issue by conducting a policy simulation.

The remainder of this paper is organized as follows. The next section provides a brief overview of relevant literature. Section 3 describes the model setup and the estimation approach and Section 4 presents the description of the data used in the study. In Section 5, the empirical analysis is discussed. Section 6 concludes the paper.

II. Literature Review

Consumer search behavior has been a major research issue in economics and marketing. The economic theory of search posits that consumers search when the benefit of searching exceeds the search cost. The seminal work of Stigler (1961) considers consumer search for price information and explains that consumers canvass various sellers in homogenous goods market to find the most favorable price. While Stigler (1961) proposed the fixed-sample strategy, Weitzman

(1979) discusses the case in which information sources with different priors are searched sequentially. He shows that the optimal search strategy is to search in order of reservation utility and to stop searching when the reward is smaller than the reservation utility. In marketing literature, Moorthy, Ratchford, and Talukdar (1997) utilize Weitzman model to explain the effect of prior brand perceptions on the search process. Several studies in marketing also discuss consumer information behavior based on the economic theory of search (see, for example, Punj and Staelin 1983; Ratchford and Srinivasan 1993).

Some studies in marketing develop structural models of optimal search and choice. Mehta et al. (2003) model consumers' consideration set formation as a result of costly information search behavior. Their paper defines a consideration set as the optimal subset of brands that a consumer decides to search for their price information. A consumer compares all possible consideration sets and chooses the set which has the largest difference between the expected maximum utility and the cost of searching information about them. Among the brands in the consideration set, she chooses the one with the maximum expected value. Erdem et al. (2005) integrate active information search into a model of consumer choice behavior. A consumer follows a Bayesian updating process for quality information from five information sources, and optimizes the choice of information source in the search process and the choice of which product to buy and when. The model is estimated using a panel dataset including information sources visited, search durations, and stated attitudes towards the alternatives during the search process. Kim et al. (2010) develop a joint model of optimal search and choice. They derive search and choice from the same economic primitives – utility and search cost – and expand the standard choice-based model to incorporate costly search. Their model is used to identify the size and composition of a consumer search set and to obtain price elasticity. In addition, they investigate the effect of reduced search cost on consumer surplus and market structure under full and limited search by counterfactual simulations. Those studies summarized above focus on the situation in which consumers search for price or quality information. However, consumers may engage in the search process to obtain information on other product attributes. Because the number of others consuming the product influences the utility of the product in the markets with network effects (Katz and Shapiro 1985), consumers may search for information on the size of the "network". There are a number of studies that include the effect of the size of the installed base when modeling consumer choice. Katz and Shapiro (1985) define consumer utility from a product as the sum of the consumer's basic willingness to pay for the product and the value she attaches to the consumption externality net of the disutility of the price. Economides and Himmelberg (1995) and Saloner and Shepard (1995) study direct network effects in the markets for FAX machines and ATM machines, respectively. Several papers such as Shankar and Bayus (2003) empirically study indirect network effects. Nair, Chintagunta and Dubé (2004) derive consumer utility in the market with indirect network effect using a constant elasticity of substitution (CES) utility framework. Indirect network externality arises because a consumer purchasing a hardware item considers that the software variety will increase with the number of hardware units sold, and the consumer's utility is a power function of the software variety. Clements and Ohashi (2005) and Liu (2010) utilize a similar specification, and Dubé, Hitsch, and Chintagunta (2010) extend Nair et al. (2004) framework to allow for dynamic adoption decisions. Consumers have expectations on the evolution of the installed base and make adoption decisions based on their expectations on the future software variety.

Lee (2013) also constructs a dynamic model to study indirect network effects in video game console industry. However, those studies do not model how consumers obtain information and form expectations on the size of network effect.

In this study, we build a dynamic structural model of optimal search and choice. The model is particularly suitable for the durable goods markets with network externalities, because we model search as pre-purchase collection of the information on the size of the network. This study shares a point with those by Mehta et al. (2003), Erdem et al. (2005), and Kim et al. (2010) in that it attempts to explain search and choice jointly by the structural modeling approach. However, our study is differentiated from them because our model is built for durable product categories with network externalities for which consumer prediction on the size of network plays a key role and their models cannot address that issue. In terms of the modeling methodology, the study by Song and Chintagunta (2003) is also related to our study. They formulate an optimal stopping problem to describe consumers' durable goods adoption behavior. In their model, a consumer has an option to purchase a product or to delay the purchase to the next time period. Once a consumer buys a product, she exits the market. We extend their model to incorporate search decision. In our framework, if a consumer delays the purchase, she participates in the search process to gain information on the size of the network and makes a decision on which brands to search.

To estimate the model, we use the online search volume data from Google Trends and the sales data. Since the web search volume data such as Google Trends have become available, researchers have been actively making use of this new type of data. Previous works utilizing Google Trends data mostly attempt to track various "trends" based on the fact that the web search volume is often correlated with the contemporaneous events. For instance, a number of papers in epidemiology show that search volume data can be used to track disease incidences. The most well-known study is Ginsberg et al. (2009), which proposes a method to analyze search volume data to track influenza-like illness. Search volume can also be linked to economic activities such as sales, unemployment, and inflation (see, for example, Ettredge et al. 2005; Goel et al. 2010; Guzman 2011; Choi and Varian 2012). In marketing literature, Du and Kamakura (2012) and Du, Hu, and Damangir (2015) describe how consumer interest and behavior can be identified from the web search volume data. Hu, Du, and Damangir (2014) use online search data to decompose the impact of advertising into two components – the impact on consumer interest in pre-purchase search and the impact on conversion of that interest into sales. Unlike the studies explained above, this study builds a structural model of individual level search and purchase decision, and explains the Google Trends data as the aggregated outcomes of individual consumer level search behaviors.

III. Model

1. Model Setup

Consider a durable product category with $j = 1, 2, ..., J$ brands available in a market with network effects. Consumers have expectations on the size of the eventual installed base of each brand, and those expectations are formed by searching the web and observing the cumulative search volume. Such web search incurs search cost to consumers. In each time period t, consumer i makes a decision on the web search and purchase. Specifically, she decides whether to purchase in time period t or to delay the purchase and search the web. The decision also includes which brands to purchase or search. The purchase alternative is denoted by $p = 0,1,2,...,J$, where $p=0$ means no purchase option. In a decision, p takes a value out of J + 1 possible values. The web search alternative is denoted by a multivariate vector $s=(s_1,s_2,...,s_J)$, where each element is a dummy indicator with $s_j=1$ indicating brand j is searched and $s_j=0$ otherwise. For convenience, the zero search alternative, $s=(0,0,...,0)$, is denoted simply by $s=0$. All alternatives are represented by the combinations of p and s in the form of p0 ($p=1,2,...,J$), 0s ($s \neq 0$), or 00. See Figure 1 for the representation of all alternatives when J = 3 brands are available in the market. Consumers evaluate the expected discounted sum of utilities for all alternatives based on the realized installed base of the brands and their expectation on future installed base, and choose the alternative that gives the largest discounted sum of expected utility.

In the initial time period, a consumer can choose "no purchase and no search" ($ps=00$) alternative. A consumer who chooses this alternative neither searches nor purchases, and remains "inactive". Once the consumer chooses an alternative other than "no search and no purchase" option, she becomes "active" and "no search and no purchase" option is no longer an option for her. This can be regarded as the beginning of a serious consideration for purchase. This approach is similar to how Chandrashekaran and Sinha (1995) model the timing of adoption. In their Split-Population Tobit (SPOT) duration model, the agents who have negative status-quo-adjusted utilities never adopt, but those who have positive utilities will eventually adopt and each individual decides the adoption timing. While the SPOT duration model of Chandrashekaran and Sinha (1995) is a reduced-form model, our study adopts a structural modeling approach. We assume that consumers single-home and there are no repeat purchases. That is, we model the first purchase only, which is not a restrictive assumption in modeling the demand for the video game consoles. Once a consumer buys a product, she does not engage in the web search or purchase process anymore. This is in line with the typical assumption that external information-seeking lasts until an actual purchase is made. (Punj and Staelin 1983) After the purchase, a consumer has no further decision to make, i.e., she exits the market. Thus, the consumer decision problem is an optimal stopping problem.

Consumer decisions are influenced by state variables. S_t denotes the vector of state variables. There are two different groups of state variables, x_t and e_t. The first group of state variables, x_t, is observable by both the consumers and the researchers. It includes the cumulative search volume of each brand, I_{jt}, and calendar time. Due to the lack of data, our study does not model how consumer expectations on

〈Figure 1〉 All alternatives when J=3 brands are available in the market

- $p=1,\ s=(0,\ 0,\ 0)$ Purchase brand 1 and exit market
- $p=2,\ s=(0,\ 0,\ 0)$ Purchase brand 2 and exit market
- $p=3,\ s=(0,\ 0,\ 0)$ Purchase brand 3 and exit market
- $p=0,\ s=(1,\ 1,\ 1)$ Delay purchase and search brand 1, 2, and 3
- $p=0,\ s=(1,\ 1,\ 0)$ Delay purchase and search brand 1 and 2
- $p=0,\ s=(1,\ 0,\ 1)$ Delay purchase and search brand 1 and 3
- $p=0,\ s=(0,\ 1,\ 1)$ Delay purchase and search brand 2 and 3
- $p=0,\ s=(1,\ 0,\ 0)$ Delay purchase and search brand 1
- $p=0,\ s=(0,\ 1,\ 0)$ Delay purchase and search brand 2
- $p=0,\ s=(0,\ 0,\ 1)$ Delay purchase and search brand 3
- $p=0,\ s=(0,\ 0,\ 0)$ Neither purchase nor search ("inactive")

product level characteristics such as price would influence their search and purchase decisions. Nevertheless, in terms of modeling, it is straightforward to incorporate the effect of such expectation in our modeling framework if price data are available. The second group, e_t, is observed by consumer for each decision but unobserved by researchers even after the realization. We assume that these unobservable states variables are consumer specific.

Next, we describe our specifications of the value of each alternative. Let W_{ips} denote the value of the alternative ps (purchase option p and web search option s) for consumer i, and δ the discount factor. If consumer i buys product j, she will get per-period utility for her intrinsic preference for brand j for all future time periods. She receives the discounted sum of the per-period utility for her lifetime. Note that the per-period utility from consuming a product is related to the size of the installed base of the product. So, consumers' evaluation of the utility requires the evaluation of the probability of brand j achieving eventually a wide enough installed base. Such evaluation of the probability utilizes the information set obtained from the web search. Note that consumers would expect that a product has a chance to gain a large installed base if many other consumers are also interested in the product. The strength of the market level interest in a product can be inferred from the cumulative web search volume that can be obtained from web services such as Google Trends. The larger the cumulative search volume is, the larger the probability that the brand will eventually achieve a wide enough installed base. Several papers including Goel et al. (2010) and Choi and Varian (2012) show that the web search volume can be useful in predicting current and future product sales. The valuation of the product is the sum of intrinsic utility and utility from the installed base. We specify the value of buying product j at time t as follows:

$$W_{ip0}(S_t) = \frac{\alpha_{ij}}{1-\delta} + \beta_i \pi(I_{jt}) + \lambda_i d_t + e_{ip0t}$$

for p = 1, 2, ..., J

where α_{ij} is the intrinsic preference that consumer i has for brand j, β_i is the sensitivity parameter for the probability that the brand will eventually achieve a wide enough installed base, I_{jt} is the cumulative search volume of brand j at time t, which represents the information set of consumers, and π is the function that links the cumulative search volume to the probability that the brand j will eventually achieve a wide enough installed base. We also include a dummy variable for holiday season, d_t. Seasonality is added to the model to reflect the possibility that the utility of the purchasing product increases during the holiday season. Lastly, e_{ip0t} is the unobserved state variable. To account for the uncertainty regarding network effects, the function π should be an S-shaped curve. In the earlier stage of a product's life cycle, there is large uncertainty about whether a brand will eventually achieve a wide enough installed base and thus, the search volume of each brand can greatly influence consumers' judgment of the brand's potential to achieve a wide installed base. This is represented in the initial part of the S-shaped curve where the shape of the function resembles the exponential growth curve. On the other hand, in the later stage of a product's life cycle, there is less uncertainty and the search volume has less effect on consumers' judgment. The latter part of the function π eventually levels off. Among various S-shape functional forms such as the logistic function, we utilize Bass diffusion model (Bass 1969) to specify the function π as follows:

$$\pi(I_{jt}^*) = \frac{1 - e^{-(n+m)I_{jt}^*}}{1 + \frac{m}{n} e^{-(n+m)I_{jt}^*}}$$

where I_{jt}^* is the adjusted cumulative search volume, i.e., I_{jt} divided by the average of the yearly search volume. Such an adjustment is required because the original Bass diffusion model is formulated in the dimension of time. This adjustment could be justified in our particular empirical application where the cumulative search volume data I_{jt} is fairly linear as shown in Figure 4. Bass diffusion model specification has a strong appeal in our case because one can utilize the benchmark parameter values from the previous studies. Using the meta-analysis by Sultan, Farley, and Lehmann (1990), we set the innovation factor $n = 0.03$ and the imitation factor $m = 0.38$. Figure 2 presents the plot of the function π.

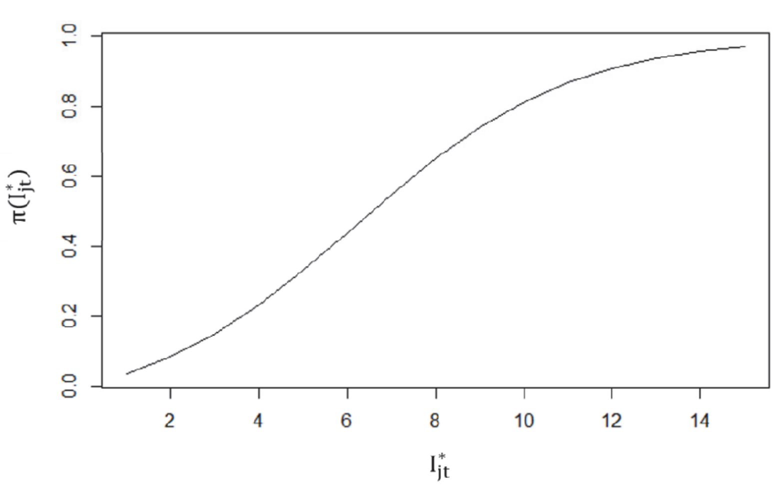
The value of delaying purchase and searching the web is the sum of (a) the discounted expected maximum value that a consumer can get at time $t+1$ with the updated information set as a result of the web search, (b) the search cost, and (c) the consumer- and time-specific unobserved term. Note that the updated information set and the search cost depend on the search option – the brand(s) that the consumer decides to search. The information set is updated only for the brand that the consumer searches, and the search cost is proportional to the number of brands to search. We also model how consumers reduce their consideration set during the web search process. Consumers may begin the process by searching any number of brands. As consumer continues the web search, she defines a reduced set of candidates and concentrates on those brands in subsequent attempts to collect information, which is in line with the model by Meyer (1982). Specifically, a consumer can only choose the alternative of purchasing or searching the brands that she searched in the previous time period. For example, if she searched brand 1 and 2 in the time period t, she only has the option to purchase brand 1, to purchase brand 2, to search brand 1 and 2, to search brand 1, or to search brand 2 in the time period $t+1$. We exclude the possibility of purchasing or searching brand 3 in $t+1$. Similarly, the option of choosing "inactive" is also excluded in future action paths. Formally, the value of delaying purchase and searching the web ($ps = 0s = 0(s_1, s_2, ..., s_J), s \neq 0$) is defined as follows:

$$W_{i0(s_1,s_2,...,s_J)}(S_t) = \delta E[\max_{p's' \in A_s}\{W_{ip's'}(S_{t+1})\}|x_t] - (\sum_{j=1}^{J} s_j)c + e_{i0(s_1,s_2,...,s_J)t}$$

$$A_s = \{(p'0),(0s') \mid p' \in \{j|s_j = 1\}, \quad s' \in \{(s'_1, s'_2, ..., s'_J)|s'_j = 0 \text{ if } s_j = 0, \quad p's' \neq 00\}$$

where c is the cost for searching a brand and $e_{i0(s_1,s_2,...,s_J)t}$ is an unobserved state variable or a random term. Here, A_s

〈Figure 2〉 Function π



denotes the set of alternatives available in the next time period to consumer who chooses the search option s. For instance, when J = 3 brands are available in the market, the value of each alternative to delay the purchase and search the web is given as:

$$\begin{aligned}W_{i0(1,1,1)}(S_t) &= \delta E[\max \\ &\{W_{i0(1,1,1)}(S_{t+1}), W_{i0(1,1,0)}(S_{t+1}), W_{i0(1,0,1)}(S_{t+1}), W_{i0(0,1,1)}(S_{t+1}), \\ &W_{i0(1,0,0)}(S_{t+1}), W_{i0(0,1,0)}(S_{t+1}), W_{i0(0,0,1)}(S_{t+1}), \\ &W_{i10}(S_{t+1}), W_{i20}(S_{t+1}), W_{i30}(S_{t+1})\} \mid x_t] - 3c + e_{i0(1,1,1)t}\end{aligned}$$

$$\begin{aligned}W_{i0(1,1,0)}(S_t) &= \delta E[\max \\ &\{W_{i0(1,1,0)}(S_{t+1}), W_{i0(1,0,0)}(S_{t+1}), W_{i0(0,1,0)}(S_{t+1}), \\ &W_{i10}(S_{t+1}), W_{i20}(S_{t+1})\} \mid x_t] - 2c + e_{i0(1,1,0)t}\end{aligned}$$

$$\begin{aligned}W_{i0(1,0,1)}(S_t) &= \delta E[\max \\ &\{W_{i0(1,0,1)}(S_{t+1}), W_{i0(1,0,0)}(S_{t+1}), W_{i0(0,0,1)}(S_{t+1}), \\ &W_{i10}(S_{t+1}), W_{i30}(S_{t+1})\} \mid x_t] - 2c + e_{i0(1,0,1)t}\end{aligned}$$

$$\begin{aligned}W_{i0(0,1,1)}(S_t) &= \delta E[\max \\ &\{W_{i0(0,1,1)}(S_{t+1}), W_{i0(0,1,0)}(S_{t+1}), W_{i0(0,0,1)}(S_{t+1}), \\ &W_{i20}(S_{t+1}), W_{i30}(S_{t+1})\} \mid x_t] - 2c + e_{i0(0,1,1)t}\end{aligned}$$

$$\begin{aligned}W_{i0(1,0,0)}(S_t) &= \delta E[\max\{W_{i0(1,0,0)}(S_{t+1}), W_{i10}(S_{t+1})\} \mid x_t] \\ &- c + e_{i0(1,0,0)t}\end{aligned}$$

$$\begin{aligned}W_{i0(0,1,0)}(S_t) &= \delta E[\max\{W_{i0(0,1,0)}(S_{t+1}), W_{i20}(S_{t+1})\} \mid x_t] \\ &- c + e_{i0(0,1,0)t}\end{aligned}$$

$$\begin{aligned}W_{i0(0,0,1)}(S_t) &= \delta E[\max\{W_{i0(0,0,1)}(S_{t+1}), W_{i30}(S_{t+1})\} \mid x_t] \\ &- c + e_{i0(0,0,1)t}\end{aligned}$$

Lastly, the value of “no search and no purchase” alternative is the value of delaying the entry to the market. The value of this alternative is the sum of (a) the discounted expected maximum value that a consumer can get at time t+1 and (b) the consumer- and time-specific unobserved term. The value of this alternative is given as:

$$W_{i00}(S_t) = \delta E[\max_{\forall p's'}\{W_{ip's'}(S_{t+1})\} | x_t] + e_{i00t}$$

When consumer chooses this alternative ($ps = 00$), there is no restriction on the set of alternatives available in the next time period. For example, when J = 3 brands are available in the market, the value of “no search and no purchase” alternative is expressed as:

$$\begin{aligned}W_{i00}(S_t) &= \delta E[\max \\ &\{W_{i00}(S_{t+1}), W_{i10}(S_{t+1}), W_{i20}(S_{t+1}), W_{i30}(S_{t+1}), \\ &W_{i0(1,1,1)}(S_{t+1}), W_{i0(1,1,0)}(S_{t+1}), W_{i0(1,0,1)}(S_{t+1}), W_{i0(0,1,1)}(S_{t+1}), \\ &W_{i0(1,0,0)}(S_{t+1}), W_{i0(0,1,0)}(S_{t+1}), W_{i0(0,0,1)}(S_{t+1})\} \mid x_t] + e_{i00t}\end{aligned}$$

We denote the observable part of each alternative as follows:

$$V_{ip0}(x_t) = \frac{\alpha_{ij}}{1-\delta} + \beta_i \pi(I_{jt}) + \lambda_i d_t \text{ for p = 1, 2, ..., J}$$

$$V_{i0(s_1,s_2,\ldots,s_J)}(x_t) = \delta E[\max_{p's' \in A_s}\{W_{ip's'}(S_{t+1})\} | x_t] - (\sum_{j=1}^{J} s_j)c$$

$$V_{i00}(x_t) = \delta E[\max_{\forall p's'}\{W_{ip's'}(S_{t+1})\} | x_t]$$

The value functions for delaying purchase options ($ps = 0s$) are computed numerically using the value function iteration procedure.

We assume that consumers rationally expect the future states and take their expectations into consideration when evaluating the discounted expected maximum value that a consumer can get at time t+1. We assume that the state evolves according to a Markov transition probability $P(S_{t+1}|S_t, D_t)$, where D_t denotes the consumer decision. Consumers are also assumed to be aware of the transition probability. We also make a standard assumption of “conditional independence”, which implies current realizations of e_t do not influence future states. (Rust 1994) The conditional independence assumption implies the transition probability can be rewritten as follows:

$$P(S_{t+1}|S_t, D_t) = P(x_{t+1}|x_t, D_t) P(e_{t+1})$$

For the first part of the right hand side of the above equation, $P(x_{t+1}|x_t, D_t)$, we assume that consumers have rational expectations on the evolution of the information set, which is represented by the cumulative web search volume, depending on their search decisions. If a consumer searches brand j, then she expects her information state regarding brand j to be updated by μ_j and to evolve according to the truncated normal distribution I_{jt+1} ~ truncated $N(I_{jt}+\mu_j, \sigma_j^2)$. On the other hand, if she does not search brand j, her information state is not updated: I_{jt+1} ~ truncated $N(I_{jt}, \sigma_j^2)$. The transition probability is a truncated distribution with the support $[I_{jt}, \infty)$, because consumers know that the cumulative web search volume does not decrease. Inactive consumers do not have expectations and they believe that the future state will be the same as the current state.

2. Estimation

The approach to estimating the parameters of the model is as follows. From the model described in the previous section, it is possible to calculate the unconditional probability that consumer i chooses alternative ps at time t, for a given value of parameter vector. Aggregating these probabilities across consumers leads to the market share of each alternative. Then the parameter estimation is done by minimizing the sum of squared differences between the observed and the predicted share of sales and search. Before discussing the estimation in detail, we need to discuss what parameters are estimated. We estimate the heterogeneous distributions of the intrinsic preference for each brand (α), the sensitivity to the installed base (β), the seasonality parameter (λ), and the search cost (c). Following the standard approach in the literature, we fix the discount factor at a constant such as 0.9. Recently a few studies attempt to estimate discount factors (see, for example, Yao, Mela, Chiang, and Chen 2012; Dubé, Hitsch, and Jindal 2014; Chung, Steenburgh, and Sudhir 2014). Such approaches require very heavy data to identify the discount factor or need to impose some identification restrictions. But our aggregate data do not fit their requirements to do so. The discount factor is assumed to be 0.9 as in Dubé, Hitsch, and Chintagunta (2010), which shares a similar context with our study in that it formulates a dynamic demand model with the expectation on the installed base in the video game console market. Regarding the transition probability parameters, we also follow the typical two-step approach, i.e., we first estimate the parameters of the transition probability (μ_j, σ_j^2) from the empirical distribution of the observed web search volume and then use the estimated transition probability parameters to estimate the sensitivity parameters in the utility function.

Now, we describe how to obtain the unconditional probability that consumer i chooses alternative ps at time t. Recall that the value for each alternative is expressed as the sum of the observable part V_{ipst} and the unobservable random term e_{ipst}. Under the assumption that the random term follows an i.i.d Type 1 extreme value distribution, the conditional choice probability that consumer i chooses alternative ps conditional on the event that the consumer has chosen the search alternative s^* in the previous time period is given as:

$$h_{ipst}^{s*} = \frac{\exp(V_{ipst})}{\sum_{p's' \in A_{s^*}} \exp(V_{ip's't})}$$

where $s*$ is the search alternative that the consumer chose in the previous time period. The set of the available alternatives (A_s) differ across consumers as explained in Section 3.1. If alternative ps is unavailable to consumer i, i.e., $ps \notin A_{s^*}$, then $h_{ipst} = 0$. Let ϕ_{ipst} be the unconditional probability that consumer i chooses alternative ps at time t. Note that, in order for consumer i to purchase or search at time t, the consumer should have not yet made any purchase. In other words, she should have engaged in search at time t-1 or have remained inactive until time t-1. So the unconditional probability can be obtained recursively from conditional probabilities as follows:

$$\phi_{ipst} = \sum_{\forall s^*} \phi_{i0s^*t-1} h_{ipst}^{s^*} \text{ for } ps \neq 00$$

$$\phi_{i00t} = (\phi_{i00t-1}) h_{i00t}^{0}$$

Then, we aggregate the above unconditional probabilities across heterogeneous consumers to obtain the market share for each alternative. Let θ_i denote the vector of the consumer-specific parameters and assume that it follows the distribution $P(\theta;\Omega)$ across consumers, where Ω is the set of hyperparameters that characterize the distribution function. The predicted market share of alternative ps at time t, Φ_{pst}, is the aggregation of the individual choice probabilities over the distribution of heterogeneous consumers $\Phi_{pst} = \int \phi_{ipst} dP(\theta;\Omega)$. With a latent class approach to model heterogeneity, the market share is obtained from $\Phi_{pst} = \sum_r \phi_{pst}(r)\gamma_r$, where γ_r is the size of the segment r. In addition, since the search share for each brand, not for each search alternative, is observed, we compute the search share for brand j by summing up the shares for the alternative with $s_j = 1$.

The model parameters – the heterogeneous distributions of the intrinsic preference for each brand (α_{ij}), the sensitivity for the installed base (β_i), the seasonality parameter (λ_i), and the search cost (c_i) – are estimated by minimizing the weighted sum of squared differences between the observed and the predicted share of sales and search. Let q_{jt} be the observed sales share and y_{jt} be the observed search share of brand j at time t. Then, the nonlinear least squares problem for the parameter estimation is given as:

$$\min_\theta \sum_j \sum_t [w_y(y_{jt} - \widehat{y_{jt}})^2 + w_q(q_{jt} - \widehat{q_{jt}})^2]$$

For numerical optimization, we use the Nelder-Mead method in the ‘optimx’ package for R. The standard errors are calculated using the sampling theory results based on a linear Taylor series approximation to the nonlinear function at the estimated parameter values. (Refer to Chapter 9 of Greene (2002).) Computational time increases in the complexity of consumer heterogeneity. We utilize the latent class approach to model consumer heterogeneity. While it takes 4 hours to estimate the homogeneous model in a standard PC, the heterogeneous model with four-segment specification needs 200 hours, which seems decent for dynamic structural model that utilizes value function iteration algorithm with aggregate data.

Ⅳ. Data

The model is applied to a data set obtained from the U.S. video game console industry, specifically the seventh generation. This generation includes three major products: Nintendo Wii, Microsoft Xbox 360, and Sony PlayStation 3. Xbox 360 was released in November 2005, and the other

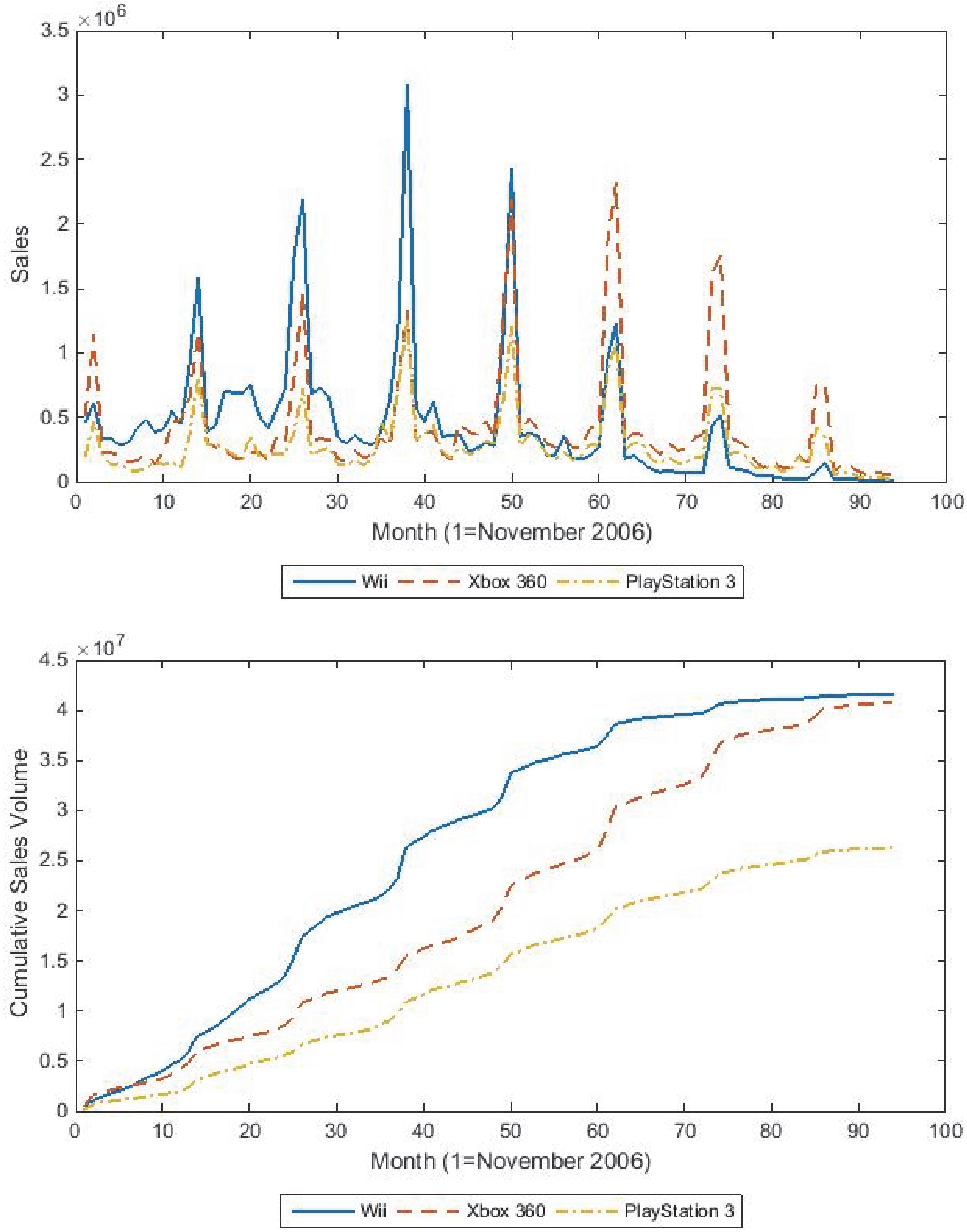
〈Table 1〉 Descriptive statistics

		Nintendo Wii	Microsoft Xbox 360	Sony PlayStation 3
Entry time		Nov 2006	Nov 2005	Nov 2006
Sales volume (units)	Total*	41,573,557	40,815,709	26,253,095
	Average	442,272	434,210	279,288
	Standard deviation	514,314	453,086	237,692
Web search volume (Google Trends index)	Total*	7,077.86	7,941.14	7,187.14
	Average	75.30	84.48	76.46
	Standard deviation	46.48	19.68	22.08

* Total sales volume and web search volume from Nov 2006 to Aug 2014.

two products were released in November 2006. The data consist of two parts: the online search volume indices and the sales of each brand. The sales data is acquired from VGChartz (http://www.vgchartz.com), a website that publishes sales estimates of video game consoles and software. For the web search volume, we utilize Google Trends data (http://www.google.com/trends/). Google Trends provides normalized the time-series indices of the percentages of the

〈Figure 3〉 Sales volume of video game consoles

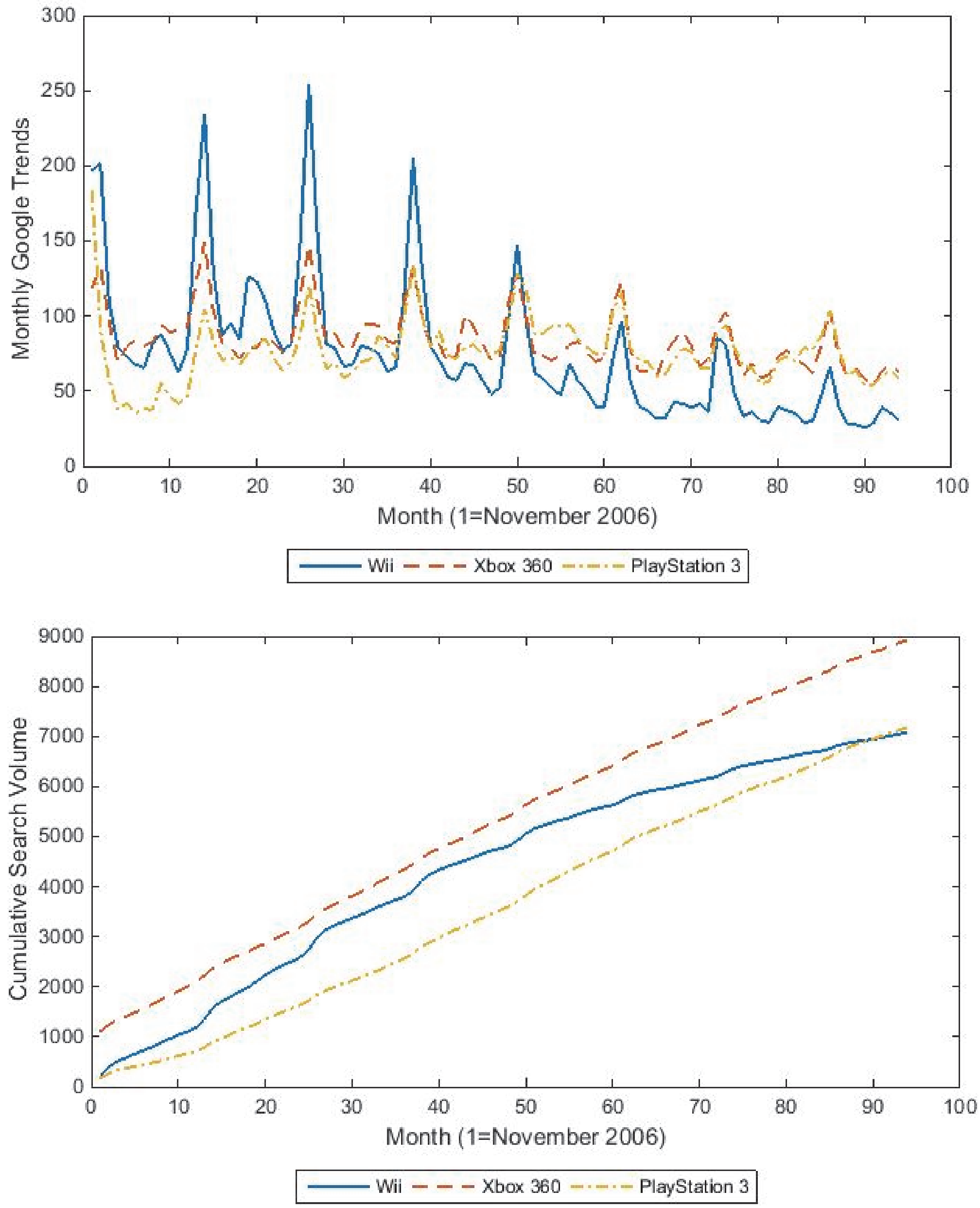


* Cumulative sales volume since November 2006

Google search volume for a specific keyword to the total Google search volume.

Although both sales and search volume data are available weekly for worldwide regions from 2004, we use the aggregated monthly observations in the U.S. from November 2006, when all three brands had become available in the market, to August 2014. Descriptive statistics are provided in Table 1, and Figure 3 and Figure 4 show the monthly observations of sales and web search volume, respectively. Both sales and web search volumes show a very strong

〈Figure 4〉 Web search volume index of video game consoles



* Cumulative search volume since launch (Xbox 360: November 2005; Wii and PlayStation 3: November 2006)

seasonality. Nintendo Wii is the largest brand in terms of sales while Microsoft Xbox 360 has more web search volumes than other brands. Sony PlayStation 3 is the smallest brand in terms of sales. Interestingly, Wii has the smallest search volume among the brand while it has the largest sales. In the early time periods, consumers appear very interested in Wii and purchase this brand. Such relatively early adoption seems to result in early take off of the brand. As consumers who intrinsically prefer Wii purchase the brand in early time periods, they exit the market earlier than other consumers. So the interest in Wii among consumers, reflected in web search volume, appears dramatically low in the later time periods as shown in Figure 4.

Note that Google Trends provide the normalized index of the search volume, not the absolute volume of web search. This fact should be considered when the observed search share from the Google Trends index is calculated in the estimation procedure. We multiply a constant to the Google Trends data and then divide by the market size, to obtain the observed search share. To determine the constant, we obtained the monthly absolute web search volume of the keyword "Wii" from March 2013 to August 2014 from Google AdWords Keyword Planner (http://www.google.com/adwords/), a service to help marketing managers build a search advertisement. Then we calculated the average ratio of the absolute web search volume to the Google Trends index of the keyword "Wii". Considering the possibility that a consumer conducts multiple web searches during each month, we set the constant as one-half of this ratio. The market size is defined as the number of the U.S. households in 2013 net of the total sales of Xbox 360 until October 2006.

Ⅴ. Empirical Analysis

1. Parameter Estimates

The estimation results are presented in Table 2. We account for consumer heterogeneity using a latent class specification. We estimate four models differing in the number of segments assumed. Given the aggregated nature of the data, likelihood based model selection criteria such as BIC are not applicable for our study. Instead, for model selection, we conduct Wald tests with a null hypothesis that the parameters for segment r are identical to those for segment r' in heterogeneous models. The null hypothesis in the test is given by $H_0 : \theta_r = \theta_{r'}$, where θ_r is the vector of the segment- specific parameters for segment r. We conduct Wald test for all possible pairs of consumer segments. If the null hypothesis cannot be rejected for a pair of consumer segments in a model, a segment is not separately identified from the other. One should be able to reject the null hypothesis if there is enough heterogeneity among consumers. If there are more segments in the model than needed, Wald test cannot reject the null hypothesis for at least a pair of segments. The Wald test results are presented in Table 3. Upto three-segment models, Wald test rejects the null hypothesis for all pairs of segment. But for the four-segment model estimation results, Wald test does not reject the null hypothesis for the pair of segments 1 and 4 and for the pair of segments 3 and 4. We conclude that the four-segment model has more segments than needed. Hence, we take the three-segment model as the final model.

We identify three consumer segments in the final model. Consumers in segment 1 (36.09%) and segment 2 (23.73%) can be labeled as *search-reliant early purchasers*. They are sensitive to the ability of brand being a popular one, i.e., the

〈Table 2〉 Estimation results

	Homogeneous Model	Two-segment Model	
		Seg. 1	Seg. 2
Wii (α)	-0.5941 (0.0054)	-0.4990 (0.0169)	-0.7602 (0.0533)
Xbox 360 (α)	-0.6224 (0.0065)	-0.6562 (0.0342)	-0.6561 (0.0270)
PlayStation 3 (α)	-0.6118 (0.0060)	-0.7354 (0.1680)	-0.6104 (0.0191)
Network Effect (β)	3.7095 (0.2488)	7.1945 (0.9611)	3.7881 (0.5151)
Seasonality (λ)	1.2154 (0.0418)	1.4698 (0.1031)	0.9705 (0.1003)
Search Cost (c)	2.0663 (0.0172)	2.2084 (0.0764)	1.9151 (0.0457)
Size of Segment	1	0.3796	0.6204
Sum of Squared Errors	534.46	414.11	

	Three-segment Model		
	Seg. 1	Seg. 2	Seg. 3
Wii (α)	-0.4835 (0.0279)	-0.8440 (0.1579)	-0.8004 (0.0890)
Xbox 360 (α)	-0.6891 (0.0893)	-0.7341 (0.1193)	-0.6325 (0.0306)
PlayStation 3 (α)	-0.8754 (0.9060)	-0.6752 (0.1033)	-0.5937 (0.0265)
Network Effect (β)	6.2969 (0.8247)	6.3086 (1.2560)	2.7852 (0.8589)
Seasonality (λ)	1.4695 (0.1515)	2.9061 (1.4621)	-0.9586 (2.1335)
Search Cost (c)	2.1625 (0.0756)	2.6565 (0.3795)	1.6839 (0.1822)
Size of Segment	0.3609	0.2373	0.4018
Sum of Squared Errors		345.06	

	Four-segment Model			
	Seg. 1	Seg. 2	Seg. 3	Seg. 4
Wii (α)	-0.4270 (0.0635)	-0.5386 (0.0285)	-0.7362 (0.0262)	-0.7709 (1.7199)
Xbox 360 (α)	-0.4773 (0.0855)	-0.9356 (0.4634)	-0.7115 (0.0275)	-0.6998 (1.9468)
PlayStation 3 (α)	-1.1997 (1.2617)	-0.9283 (0.5638)	-0.6903 (0.0184)	-0.6283 (2.2408)
Network Effect (β)	5.7626 (1.3749)	11.7385 (0.9584)	7.0328 (0.8116)	4.0933 (2.5437)
Seasonality (λ)	1.1256 (0.3456)	1.6274 (0.2886)	2.3791 (0.1997)	0.6308 (3.0542)
Search Cost (c)	1.6221 (0.2782)	2.3562 (0.3214)	4.6237 (0.4845)	1.7171 (3.5958)
Size of Segment	0.1066	0.1695	0.2522	0.4717
Sum of Squared Errors		296.79		

〈Table 3〉 Results for Wald test

	H_0	Wald statistic	p-value
Two-segment Model	$\theta_1 = \theta_2$	216.4485	〈 0.001
Three-segment Model	$\theta_1 = \theta_2$	14.0501	0.0291
	$\theta_1 = \theta_3$	25.4864	〈 0.001
	$\theta_2 = \theta_3$	53.2217	〈 0.001
Four-segment Model	$\theta_1 = \theta_2$	170.5759	〈 0.001
	$\theta_1 = \theta_3$	97.7569	〈 0.001
	$\theta_1 = \theta_4$	0.7787	0.9926
	$\theta_2 = \theta_3$	161.6999	〈 0.001
	$\theta_2 = \theta_4$	13.7567	0.0325
	$\theta_3 = \theta_4$	3.0626	0.8009

probability that the brand will eventually achieve a wide enough installed base (β=6.2969 for segment 1 and β= 6.3086 for segment 2). Even though they have a small piece of evidence that the brand will eventually achieve a wide enough installed base, they take it very important. This large sensitivity, together with their large search cost (c=2.1625 for segment 1 and c=2.6565 for segment 2), leads to early purchase. That is, these consumers have large initial benefit from search and large cost for additional searches. In addition, the large sensitivity to the ability of brand being a popular one strongly influences these consumers' brand choice. Because they anticipate the popular brand by searching the web, they are more likely to purchase the brand with the favorable search result. Though consumers in segment 1 and in segment 2 share characteristics regarding search behavior, they have different intrinsic preferences for brands. Consumers in segment 1 have a high preference for the Wii brand, and thus, they mostly search for and purchase the Wii. On the other hand, consumers in segment 2 have the highest preference for PlayStation 3 and the lowest preference for Wii. Consumers in segment 3 (40.18%) can be labeled as *careful searchers*. In contrast to consumers in segments 1 and 2, consumers in segment 3 do not derive much utility from a small probability of a brand achieving a wide enough installed base (β=2.7852). And they have a small search cost (c=1.6839). So they delay purchase and continue the web search until they have enough information sufficient to guarantee large network size. Like consumers in segment 2, consumers in segment 3 have the highest intrinsic preference for PlayStation 3 and the lowest intrinsic preference for Wii. They mostly search for and purchase the Xbox 360 and PlayStation 3. Note that this group of consumers does not have a significant seasonality parameter.

Our identification of heterogeneous consumer segments can provide some insights for marketing managers in this market. Early adopters for video game consoles have a large search cost but they are sensitive to the probability that a brand will become a popular platform. So, in the early periods of the product life cycle for this product category, marketers should provide cues assuring the possibility of their brand achieving a wide installed base. And since these consumers are sensitive to seasonality, marketers may want to allocate their advertising budget more for holiday seasons. Meanwhile, late adopters have a small search cost and they are likely to search many brands. The intrinsic brand preferences play a relatively more important role than the sensitivity to the probability of the brand popularity in these consumers' purchase decisions.

2. Policy Simulation

Given the nature of the structural modeling approach, one can utilize policy simulation approaches to draw managerial insights from the model. Since our model is on consumer web search behaviors, keyword search advertising would be a direct area that our model can be applied to. Based on the parameter estimates of the three-segment model, we conduct policy experiments on keyword search advertising. Keyword search advertising has become an important research topic, because it is a dominant form of online advertising. Many studies including Edelman, Ostrovsky, and Schwarz (2007) and Varian (2007) focus on how the search advertising slots are sold via an auction mechanism. Researchers have also investigated issues related to keyword search advertising in connection with consumer search through analytic modeling approaches (see, for example, Athey and Ellison 2011; Chen and He 2011; Desai, Shin, and Staelin 2014). Selecting keywords for search advertising is an interesting problem, but has been given little attention (Rutz and Bucklin 2011; Desai et al. 2014). In particular, Desai et al.

(2014) identified the benefits and costs of purchasing one's own brand name or a competitor's brand name as a keyword.

From an empirical perspective, we investigate the effect of purchasing a competitor's brand name as a keyword for search advertising. Unlike the paper of Desai et al. (2014) which focuses on the impact of search advertising on consumers' quality perceptions, we assume that purchasing a competitor's brand name as a keyword affects consumers' consideration set in order to be consistent with our settings. For example, a consumer who has only considered purchasing a Sony PlayStation 3 may search for Sony PlayStation 3. But if this consumer is somehow exposed to advertising for Xbox 360, then she might begin to consider Xbox 360 as a candidate product. The impact of advertising on consumers' consideration set has been well demonstrated in numerous studies such as Yoo (2008) and Terui, Ban, and Allenby (2011).

Note that our model can accommodate changes in a consumer's consideration set. Recall that in the model, a consumer can only choose the alternative of purchasing or searching for the brands that she searched in the previous time period. The set of alternatives available to a consumer who chose the search option s was denoted by A_s. The brands included in this set can be regarded as brands in a consideration set. In the policy simulation setting, we assume that the exposure to search advertising expands consumers' consideration set. For example, if a consumer searched for brand 1 in the previous time period and was not exposed to search advertising, she only has the option to purchase brand 1, or to search for brand 1 further to check if the brand is likely to be the popular brand. However, if she searched for brand 1 in the previous time period and was exposed to search advertising of brand 2, then she has the option to purchase brand 1, to purchase brand 2, to search for brands 1 and 2, to search for brand 1, or to search for brand 2. That is, she has an expanded set A_s.

In the policy simulation, we compute the sales impact of purchasing a competitor's brand name as a search advertising keyword for the entire time period since November 2006. There are three brands in the market, so two keyword options are available for each firm. For example, "Xbox 360" and "PlayStation 3" are the available keywords for Nintendo. Nintendo has four options for keyword purchase: (1) buy both "Xbox 360" and "PlayStation 3", (2) buy "Xbox 360" only, (3) buy "PlayStation 3" only, and (4) buy neither. If Nintendo purchases "Xbox 360", a consumer who searches for "Xbox 360" will be exposed to an advertisement for "Nintendo". Since each firm has four options, there are 64 possible cases based on the interaction among three firms. Table 4 shows the results for this policy simulation. Each row corresponds to a case. The circle indicates the firms' keyword purchasing decisions. We compute the cumulative sales of each brand from November 2006 to July 2014, and the market share of each brand for each case. The first row is the benchmark case where no firm purchases competitors' keyword. The arrows next to the numbers indicate the direction of change compared to the benchmark case.

The sales for the firms that purchase a search advertising keyword tend to increase in most cases. However, there is a possibility that the sales increase is an inter-temporal effect of search advertising. Note that the total category sales in all cases with any keyword purchase are larger than in the benchmark case. That is, the keyword purchase effect is simply due to the more advertising that would result in purchase acceleration at the category level. Hence, we analyze the impact of purchasing a competitor's brand name as a search advertising keyword on both sales and market shares in order to figure out the brand switching effect as well. When only one firm advertises (Table 4, Rows 2-10), the

〈Table 4〉 The effect of purchasing a competitor's brand name as a keyword for search advertising

Advertising Firm:	Nintendo (Wii)		Microsoft (Xbox)		Sony (PlayStation)		Sales (10^6 Unit)							Market Share					
Keyword:	Xbox	PS3	Wii	PS3	Wii	Xbox	Wii		Xbox		PS3		Total	Wii		Xbox		PS3	
1							41.75	(=)	38.50	(=)	27.53	(=)	107.79	38.73%	(=)	35.72%	(=)	25.54%	(=)
2	O						44.78	(↑)	36.74	(↓)	26.90	(↓)	108.43	41.30%	(↑)	33.89%	(↓)	24.81%	(↓)
3		O					44.63	(↑)	36.78	(↓)	27.01	(↓)	108.42	41.16%	(↑)	33.93%	(↓)	24.91%	(↓)
4			O				39.87	(↓)	45.57	(↑)	24.96	(↓)	110.40	36.11%	(↓)	41.28%	(↑)	22.61%	(↓)
5				O			40.05	(↓)	45.59	(↑)	24.62	(↓)	110.27	36.32%	(↓)	41.35%	(↑)	22.33%	(↓)
6					O		40.94	(↓)	35.61	(↓)	33.73	(↑)	110.28	37.12%	(↓)	32.29%	(↓)	30.58%	(↑)
7						O	41.20	(↓)	35.40	(↓)	33.55	(↑)	110.15	37.40%	(↓)	32.14%	(↓)	30.46%	(↑)
8	O	O					47.03	(↑)	35.44	(↓)	26.46	(↓)	108.93	43.18%	(↑)	32.54%	(↓)	24.29%	(↓)
9			O	O			38.47	(↓)	50.83	(↑)	22.74	(↓)	112.04	34.33%	(↓)	45.37%	(↑)	20.30%	(↓)
10					O	O	40.52	(↓)	33.24	(↓)	38.09	(↑)	111.85	36.23%	(↓)	29.72%	(↓)	34.05%	(↑)
11			O		O		39.37	(↓)	42.31	(↑)	30.70	(↑)	112.38	35.03%	(↓)	37.65%	(↑)	27.32%	(↑)
12	O					O	44.08	(↑)	33.56	(↓)	33.24	(↑)	110.89	39.75%	(↑)	30.27%	(↓)	29.98%	(↑)
13		O		O			43.00	(↑)	43.88	(↑)	24.11	(↓)	111.00	38.74%	(↑)	39.54%	(↑)	21.72%	(↓)
14	O		O				43.19	(↑)	45.89	(↑)	23.06	(↓)	112.13	38.52%	(↓)	40.92%	(↑)	20.56%	(↓)
15		O			O		44.12	(↑)	32.33	(↓)	35.54	(↑)	112.00	39.40%	(↑)	28.87%	(↓)	31.73%	(↑)
16				O		O	38.94	(↓)	43.24	(↑)	31.25	(↑)	113.43	34.33%	(↓)	38.12%	(↑)	27.55%	(↑)
17		O	O				42.15	(↑)	46.12	(↑)	23.39	(↓)	111.66	37.75%	(↓)	41.31%	(↑)	20.95%	(↓)
18	O			O			44.00	(↑)	43.06	(↑)	23.88	(↓)	110.94	39.67%	(↑)	38.81%	(↑)	21.52%	(↓)
19	O				O		43.44	(↑)	32.73	(↓)	35.36	(↑)	111.53	38.95%	(↑)	29.35%	(↓)	31.71%	(↑)
20				O	O		38.95	(↓)	44.63	(↑)	29.16	(↑)	112.74	34.54%	(↓)	39.59%	(↑)	25.87%	(↑)
21		O				O	44.86	(↑)	33.27	(↓)	32.69	(↑)	110.83	40.48%	(↑)	30.02%	(↓)	29.50%	(↑)
22			O			O	39.26	(↓)	40.75	(↑)	32.71	(↑)	112.72	34.83%	(↓)	36.15%	(↑)	29.02%	(↑)
23	O	O	O				44.93	(↑)	46.51	(↑)	21.66	(↓)	113.10	39.73%	(↑)	41.12%	(↑)	19.15%	(↓)
24	O	O		O			46.08	(↑)	41.96	(↑)	23.47	(↓)	111.51	41.33%	(↑)	37.63%	(↑)	21.05%	(↓)
25	O		O	O			42.51	(↑)	50.47	(↑)	20.72	(↓)	113.69	37.39%	(↓)	44.39%	(↑)	18.22%	(↓)
26		O	O	O			40.95	(↓)	50.60	(↑)	21.59	(↓)	113.14	36.19%	(↓)	44.72%	(↑)	19.08%	(↓)
27	O	O			O		46.06	(↑)	30.00	(↓)	36.90	(↑)	112.96	40.77%	(↑)	26.56%	(↓)	32.67%	(↑)
28	O		O		O		42.30	(↑)	40.51	(↑)	31.68	(↑)	114.49	36.94%	(↓)	35.38%	(↓)	27.67%	(↑)
29		O	O		O		42.10	(↑)	41.84	(↑)	30.55	(↑)	114.49	36.77%	(↓)	36.54%	(↑)	26.69%	(↑)
30	O			O	O		42.37	(↑)	41.03	(↑)	30.94	(↑)	114.34	37.06%	(↓)	35.89%	(↑)	27.06%	(↑)
31		O		O	O		42.11	(↑)	41.85	(↑)	30.53	(↑)	114.49	36.78%	(↓)	36.55%	(↑)	26.67%	(↑)
32			O	O	O		37.71	(↓)	49.04	(↑)	27.25	(↓)	114.01	33.08%	(↓)	43.02%	(↑)	23.90%	(↓)
33	O	O				O	46.89	(↑)	32.05	(↓)	32.47	(↑)	111.41	42.09%	(↑)	28.77%	(↓)	29.14%	(↑)
34	O		O			O	42.29	(↑)	40.47	(↑)	31.75	(↑)	114.50	36.93%	(↓)	35.34%	(↓)	27.72%	(↑)
35		O	O			O	42.32	(↑)	41.00	(↑)	31.02	(↑)	114.34	37.02%	(↓)	35.86%	(↑)	27.13%	(↑)
36	O			O		O	42.89	(↑)	40.73	(↑)	30.70	(↑)	114.32	37.52%	(↓)	35.63%	(↓)	26.85%	(↑)
37		O		O		O	42.86	(↑)	40.76	(↑)	30.70	(↑)	114.32	37.49%	(↓)	35.65%	(↓)	26.86%	(↑)
38			O	O		O	37.32	(↓)	47.03	(↑)	30.61	(↑)	114.96	32.46%	(↓)	40.91%	(↑)	26.63%	(↑)
39	O				O	O	43.01	(↑)	30.70	(↓)	39.26	(↑)	112.97	38.07%	(↓)	27.18%	(↓)	34.75%	(↑)
40		O			O	O	44.29	(↑)	29.57	(↓)	39.65	(↑)	113.52	39.02%	(↑)	26.05%	(↓)	34.93%	(↑)
41			O		O	O	38.90	(↓)	38.64	(↑)	36.39	(↑)	113.93	34.14%	(↓)	33.91%	(↓)	31.94%	(↑)
42				O	O	O	38.03	(↓)	42.48	(↑)	34.41	(↑)	114.91	33.09%	(↓)	36.96%	(↑)	29.94%	(↑)
43	O	O	O	O			44.19	(↑)	50.47	(↑)	19.81	(↓)	114.47	38.61%	(↓)	44.09%	(↑)	17.30%	(↓)
44	O	O	O		O		44.50	(↑)	40.22	(↑)	31.33	(↑)	116.04	38.34%	(↓)	34.66%	(↓)	27.00%	(↑)
45	O	O		O	O		44.71	(↑)	38.89	(↑)	32.07	(↑)	115.67	38.65%	(↓)	33.63%	(↓)	27.72%	(↑)
46	O		O	O	O		41.40	(↓)	46.63	(↑)	28.15	(↑)	116.18	35.64%	(↓)	40.13%	(↑)	24.23%	(↓)
47		O	O	O	O		40.60	(↓)	47.69	(↑)	27.58	(↑)	115.87	35.04%	(↓)	41.16%	(↑)	23.80%	(↓)
48	O	O	O			O	44.57	(↑)	41.02	(↑)	30.10	(↑)	115.69	38.53%	(↓)	35.46%	(↓)	26.02%	(↑)
49	O	O		O		O	45.52	(↑)	39.20	(↑)	30.26	(↑)	114.99	39.59%	(↑)	34.09%	(↓)	26.32%	(↑)
50	O		O	O		O	41.24	(↓)	45.96	(↑)	29.32	(↑)	116.52	35.39%	(↓)	39.44%	(↑)	25.17%	(↓)
51		O	O	O		O	40.76	(↓)	46.02	(↑)	29.51	(↑)	116.30	35.05%	(↓)	39.57%	(↑)	25.38%	(↓)
52	O	O			O	O	45.96	(↑)	27.83	(↓)	40.51	(↑)	114.30	40.21%	(↑)	24.35%	(↓)	35.44%	(↑)
53	O		O		O	O	41.72	(↓)	37.20	(↓)	36.91	(↑)	115.83	36.02%	(↓)	32.12%	(↓)	31.87%	(↑)
54		O	O		O	O	42.25	(↑)	37.67	(↓)	36.20	(↑)	116.12	36.39%	(↓)	32.44%	(↓)	31.18%	(↑)
55	O			O	O	O	41.57	(↓)	39.22	(↑)	35.46	(↑)	116.25	35.76%	(↓)	33.74%	(↓)	30.50%	(↑)
56		O		O	O	O	41.98	(↑)	38.86	(↑)	35.62	(↑)	116.47	36.05%	(↓)	33.37%	(↓)	30.59%	(↑)
57			O	O	O	O	36.74	(↓)	45.89	(↑)	33.35	(↑)	115.98	31.68%	(↓)	39.57%	(↑)	28.75%	(↑)
58	O	O	O	O	O		43.45	(↑)	45.54	(↑)	28.34	(↑)	117.33	37.03%	(↓)	38.81%	(↑)	24.16%	(↓)
59	O	O	O	O		O	43.45	(↑)	45.50	(↑)	28.40	(↑)	117.35	37.02%	(↓)	38.77%	(↑)	24.20%	(↓)
60	O	O	O		O	O	44.24	(↑)	36.71	(↓)	36.34	(↑)	117.30	37.72%	(↓)	31.30%	(↓)	30.98%	(↑)
61	O	O		O	O	O	44.25	(↑)	36.72	(↓)	36.32	(↑)	117.30	37.72%	(↓)	31.31%	(↓)	30.97%	(↑)
62	O		O	O	O	O	40.50	(↓)	43.59	(↑)	33.55	(↑)	117.64	34.43%	(↓)	37.05%	(↑)	28.52%	(↑)
63		O	O	O	O	O	40.47	(↓)	43.61	(↑)	33.55	(↑)	117.63	34.40%	(↓)	37.08%	(↑)	28.52%	(↑)
64	O	O	O	O	O	O	42.90	(↑)	42.12	(↑)	33.42	(↑)	118.45	36.22%	(↓)	35.56%	(↓)	28.22%	(↑)

〈Table 5〉 The impact of Microsoft purchasing "Wii" as a keyword on each consumer segment

		Sales (10^6 unit)				Market Share in Each Segment		
		Wii	Xbox	PS3	Total	Wii	Xbox	PS3
Without search advertising	Segment 1	35.86	6.73	0.52	43.119	83.2%	15.6%	1.2%
	Segment 2	3.05	14.43	10.04	27.510	11.1%	52.4%	36.5%
	Segment 3	2.84	17.35	16.97	37.159	7.6%	46.7%	45.7%
Microsoft purchases "Wii"	Segment 1	34.77	7.85	0.51	43.128	80.6%	18.2%	1.2%
	Segment 2	2.84	15.19	9.58	27.610	10.3%	55.0%	34.7%
	Segment 3	2.26	22.53	14.88	39.663	5.7%	56.8%	37.5%

market share for the advertising firm increases and the market share for firms without advertising decreases. For instance, when Microsoft purchases "Wii" as the keyword (Table 4, Row 4), the market share for Xbox 360 increases from 35.72% to 41.28%. This increase is mainly derived from consumer segment 3 rather than from segment 1 (see Table 5). Because consumers in segment 1 are likely to search for the keyword "Wii", one might predict that Microsoft's purchase of the keyword "Wii" will have the largest impact on consumers in segment 1. However, the exposure of consumers in this segment to the search advertisement for Xbox 360 under the keyword "Wii" does not lead to a large sales increase of Xbox 360. Although consumers in this segment include Xbox 360 in their consideration set after being exposed to the search advertisement, they do not purchase Xbox 360 because of high intrinsic preference for Wii and relatively low intrinsic preference for Xbox 360. This result shows that significant exposure itself is not sufficient; the firm should select the keyword so that exposure to keyword search advertising leads to sales.

As demonstrated in the case, keyword search advertising does not always lead to the market share increase. Market share changes become more complicated when multiple firms advertise with multiple keywords. For example, when Nintendo purchases "Xbox 360" as a keyword and Microsoft purchases "Wii" (Table 4, Row 14), the market share for Wii decreases even though Nintendo purchases a search advertising keyword. Sales increases for both Wii and Xbox 360, but the amount of increase of Wii sales is not sufficient for the market share to be increased. Besides, it is even possible that the sales of the advertising firm decrease (Table 4, Rows 60-63). Rows 60-61 of Table 4 demonstrate such cases. The sales of Xbox 360 decrease when Microsoft purchases a search advertising keyword, because other firms – Nintendo and Sony – also advertise aggressively.

We can draw two managerial implications from the policy simulation. First, a firm that considers purchasing a competitor's brand name as a keyword should consider the search volume of the keyword and the competitive advantage of its brand over competing brands in terms of the intrinsic brand preference. A large search volume of the keyword will lead to a large amount of exposure of the search advertisement, and a decent level of competitive advantage will ensure that the exposure leads to purchase. However, if the competitor's brand is much stronger than the firm's own brand, it is possible that the exposure does not result in purchase. Second, the impact of search advertising depends on the competing firms' search advertising strategies. When firms develop keyword search advertising strategies, they should incorporate other firms' strategies, such as which firms invest in search advertising and which keywords they use. Drawing up a plan for keyword search advertising is not an easy task. This study provides tools for empirically quantifying the impact of keyword search advertising on sales and market share.

Ⅵ. Conclusion

This study formulates an empirical model of web search and purchase behaviors through a structural modeling framework of consumers' dynamic utility maximization. The proposed model is applied to the video game console industry. This study contributes to the marketing literature along both methodological and substantial dimensions. From the methodological side, this study conceptualizes and develops an estimable structural model that explains how web search volumes and sales are related. The model can be estimated using aggregate data from two different sources – online search volume and sales. From a substantial perspective, this study provides implications for firms' keyword search advertising strategies. When a firm purchases a competitor's brand name as a keyword, the search volume of the keyword and the nature of competition between the firm itself and the competitor should be considered. We also demonstrate that the impact of search advertising depends on the competing firms' search advertising strategies.

Despite the contributions, this study still has some limitations. First, it assumes that consumers search online prior to purchasing goods and that they do not search after purchasing. Second, it assumes that there are no repeat purchases. Future research may reduce or eliminate these assumptions through extending the proposed model to individual consumer level search and adoption data. Third, we assume that the purpose of the web search is limited to the installed base information and only focus on how the expectations on the installed base influence the consumer decisions. For high technology products such as video game consoles, consumers may anticipate price drops, quality increase, or launch of the next generation products such as Wii U, Xbox One, and PlayStation 4 and search for information on them. Though we do not consider how the expectations on price, quality, and product availability influence the consumer decisions due to the lack of data, it would be an interesting venue for future research to incorporate the impact of consumer expectation on such product level characteristics on consumer search and purchase decisions. Fourth, this study does not consider endogeneity in supply side behavior. It is widely known that firms have incentives to build dynamic advertising plans when they launch new products (Krishnan and Jain 2006). It would be interesting for future studies to derive the optimal dynamic advertising policy with consideration of forward-looking consumers' web search and purchase behaviors. Lastly, in the policy simulation, we assume that keyword search advertising serves the role of expanding consumers' consideration set and analyze the impact of purchasing a competitor's brand name as a keyword. However, the impact of keyword search advertising on consumers' consideration set can be relatively weak in the video game console industry, where only a few major players dominate the market and organic search results for a brand often contain information about competing brands together. It is possible that keyword search advertising also affects consumers' search cost, especially when a firm purchases its own brand name as a keyword. An avenue for future research would be to extend our work to allow for the brand specific search cost and conduct policy experiment regarding the impact of keyword search advertising on the search costs.

〈최초투고일: 2015년 4월 2일〉
〈수정일: 1차: 2015년 6월 9일〉
〈게재확정일: 2015년 6월 19일〉

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