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Web Search and Purchase Behavior in Durable Goods Markets with Network Effects

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이 논문을 경영학 석사학위논문으로 제출함

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Abstract

I develop a dynamic structural model to explain consumers' web search and purchase behavior in adoption of a new durable product in markets with network effects. In the model, consumers engage in pre-purchase web searches to form expectations on the network size of each brand, and optimize their purchase timing and brand choice based on those expectations. Decisions on web searches and purchases are the outcome of dynamic utility maximizing behavior. I apply the model to the online search volume data from Google Trends and the sales data from the U.S. video game console industry. The model is estimated with Nested Fixed Point algorithm, and the estimation results indicate that consumers are classified into three segments with different intrinsic preferences for each brand, sensitivity to information from web search, and search cost. In a policy simulation, I 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 information search; new product adoption; network effects; dynamic structural models
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1. Introduction

Most consumers who are considering the purchase of durable goods engage in information search process. Especially in a market for durable products with network effects, it can be expected that consumers will search for information regarding the number of other consumers using the product. 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 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.[1]

Considering the increase of web searching in the pre-purchase stage, it is important to understand consumers' web search behavior and how it influences their purchase decisions. This issue is of a great 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 gathered information in their purchase decisions can provide insights to marketing managers who develop search advertising strategies.

Consumers' information search behavior has been an important topic in the extant literature in economics and marketing. 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

[1] See Gomez (2013)

economic cost-benefit framework (Stigler 1961; Weitzman 1979), a number of papers in marketing discuss consumer information search and purchase choice. In particular, several papers attempt to do so by adopting a structural modeling approach. (Mehta, Rajiv, and Srinivasan 2003; Erdem, Keane, Öncü, and Strebel 2005; Kim, Albuquerque, and Bronnenberg 2010) I also build a dynamic structural model to describe consumer search and purchase behavior; however, this paper is different from the previous papers and is unique in that it explores how web search volume and sales are related.

The objective of this study is to build 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, and consumers form beliefs about the size of the installed base 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 are sure that the size of the installed base has reached an acceptable level. Thus, forward-looking consumers optimize purchase timing between early purchase with large uncertainty in the installed base and late purchase with less uncertainty as a result of 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. The results reveal that the model presented in this paper can explain consumers' web search and purchase behavior. I account for consumer heterogeneity by a latent class specification, and show that consumers are classified into

three segments with different intrinsic preferences for each brand, sensitivity to information from web search, and search cost. In a policy simulation, I quantify the impact of purchasing a competitor's brand name as a keyword for search advertising. Then I draw managerial implications regarding keyword search advertising strategies.

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

2. Literature Review

Consumer search behavior has been a major research issue in economics and marketing. The economic theory of search relies on the statement 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 canvas 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. A number of papers in marketing also discuss consumer information behavior based on the economic theory of search. (Punj and Staelin 1983; Ratchford and Srinivasan 1993)

Several studies in marketing attempt to develop structural models of optimal search and choice. Firstly, Mehta et al. (2003) discuss consumers' consideration set formation as a result of costly information search behavior. This 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. Using their model, they analyze the size and composition of a consumer search set and 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.

The 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 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. 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. Liu (2010) utilizes a similar specification, and Dubé, Hitsch, and Chintagunta (2010) extend Nair et al. (2004)'s 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. However, these studies do not model how consumers obtain information and form expectations on the size of installed base.

In this paper, I build a dynamic structural model of optimal search and choice. The model is appropriate for the durable goods industry in which network effect is significant, because I model search as pre-purchase search for the information on the size of the network. My model is similar to those of 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, regarding the product category, it is different from Mehta et al. (2003), because their model is applied to nondurable goods such as liquid detergents. I focus on the alternatives considered during the search process, as Mehta et al. (2003) and Kim et al. (2010) did, while Erdem et al. (2005) describe how consumers choose which information sources to search. In addition, unlike other studies that model consumer search for price or quality information, this study deals with consumer search for information on the network size of a product.

In terms of the modeling methodology, Song and Chintagunta (2003) is the most closely related to this 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. I extend their model to incorporate search decision. 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.

3. Model

3.1. Model Setup

Consider a durable product category with $j = 1, 2, \ldots, J$ brands available in a market with network effects. Consumers have expectations over the size of the installed base of each brand, and those expectations are formed by searching the web and seeing the cumulative search volume, which incurs search cost. 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 in time period $t + 1$, and which brands to search or purchase. The purchase alternative is denoted by $p = 0, 1, 2, \ldots, J$, where $p = 0$ means no purchase option. The web search alternative is denoted by $s = (s_1, s_2, \ldots, s_J)$, where $s_j = 1$ if the alternative is to search brand j and $s_j = 0$ otherwise. For convenience, $s = (0,0, \ldots, 0)$ alternative is denoted simply by $s = 0$. All alternatives are represented by the combinations of p and s in the form of $p0$ ($p = 1, 2, \ldots, J$), $0s$ ($s \neq 0$), or 00. (See Figure 1 for 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 search and no purchase" ($ps = 00$) 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 available for her. This can be regarded as the beginning of a serious consideration for purchase. This concept 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, I use a structural modeling approach.

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")

I assume that consumers single-home and there are no repeat purchases. 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.

S_t denotes all 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. The second group, e_t, is observed by consumer for each decision but unobserved by researchers even after the realization. I assume that these variables are consumer specific.

Now, I will explain the value of each alternative. Denote W_{ips} as the value of the alternative ps (purchase option p and web search option s) for consumer i, and δ as the discount factor. First, 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. She also gets utility from the size of the installed base. She evaluates the probability of whether the brand j will eventually achieve a wide enough installed base, using the realized information set from the web search. I assume that the richness of the information about the installed base from the web search is proportional to the cumulative web search volume. Thus, a consumer's information set is represented by the cumulative search volume of each brand. The larger the cumulative search volume is, the larger the probability that the brand will eventually achieve a wide enough installed base. The valuation of the product is the sum of intrinsic utility and utility from the installed base. I assume that the value of buying product j at time t is given by:

$$W_{ip0}(S_t) = \frac{\alpha_{ij}}{1-\delta} + \beta_i \pi(I_{jt}) + \lambda_i d_t + e_{ip0t} \quad \text{for } p = 1, 2, \dots, J$$

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 of the cumulative search volume to evaluate the probability that the brand j will eventually achieve a wide enough installed base. I assume that the function π follows the form of the installed base fraction from the Bass diffusion model (Bass 1969) with the innovation factor $p = 0.03$ and the imitation factor $q = 0.38$ (Sultan, Farley, and Lehmann 1990):

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

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 Bass diffusion model is a function of time. In addition, d_t is a seasonal dummy variable indicating the holiday season and λ_i is the sensitivity parameter for seasonality. Seasonality is added to the model to reflect the possibility that the utility of the product increases during the holiday season. Lastly, e_{ip0t} is the unobserved state variable.

Second, 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. I 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 similar to what Meyer (1982) suggested. In the model, 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 $t+1$. She cannot purchase or search brand 3 in $t+1$. Also, she cannot choose to be "inactive". Formally, the value of delaying purchase and searching the web ($\mathrm{ps} = 0\mathrm{s} = 0(\mathrm{s}_1, s_2, \dots, s_J),\ \mathrm{s} \neq 0$) is defined as follows:

$$\mathrm{W}_{\mathrm{i}0(\mathrm{s}_1,s_2,\dots,s_J)}(S_t) = \delta E\left[\max_{p's' \in A_s}\{W_{ip's'}(S_{t+1})\}\middle| x_t\right] - \left(\sum_{j=1}^{J} s_j\right)c + e_{\mathrm{i}0(\mathrm{s}_1,s_2,\dots,s_J)t}$$

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

where c is the cost for searching one brand and $\mathrm{e}_{\mathrm{i}0(\mathrm{s}_1,\mathrm{s}_2,\dots,\mathrm{s}_\mathrm{J})t}$ is an unobserved state variable or a random term. Here, $\mathrm{A_s}$ denotes the set of alternatives available in the next time period to consumer who chooses the search option s. For instance, when $\mathrm{J} = 3$ brands are available in the

market, the value of each alternative to delay the purchase and search the web is given as:

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

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

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

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

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

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

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

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:

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

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:

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

I will denote the observable part of each alternative as follows:

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

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

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

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

Consumers anticipate future states and utilize the anticipation when evaluating the discounted expected maximum value that a consumer can get at time $t+1$. The model assumption is that consumers believe that the state evolves according to the probability distribution $\mathrm{P}(S_{t+1}|S_t, D_t)$, where $\mathrm{D_t}$ denotes the consumer decision. This is a Markov distribution, because the transition of the state depends only on the current state and decision, not on the whole history of the process. I also assume "conditional independence", which implies current realizations of $\mathrm{e_t}$ do not influence

future states. (Rust 1994) Given these assumptions, the transition probability can be written as follows:

$$\mathrm{P}(\mathrm{S}_{t+1}|S_t, D_t) = P(x_{t+1}|x_t, D_t)\mathrm{P}(\mathrm{e}_{t+1})$$

For the first part of the right hand side of the above equation, $\mathrm{P}(\mathrm{x}_{t+1}|x_t, D_t)$, I 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 $\mathrm{I}_{jt+1} \sim$ 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: $\mathrm{I}_{jt+1} \sim$ truncated $N(I_{jt}, \sigma_j^2)$. The transition probability is a truncated distribution with the support $[\mathrm{I}_{jt}, \infty)$, 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.

3.2. 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. By aggregating these probabilities, I obtain the market share of each alternative. Then, I estimate the parameters of the model by minimizing the sum of squared differences between the observed and the predicted share of sales and search.

First, I explain 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 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 available alternatives (A_s) differ among consumers according to the alternative that the consumer chose in the previous time period. It is because the value of delaying purchase and searching the web depends on the available alternatives in the next time period, as it was 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. 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 as follows:

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

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

Then, I aggregate the above unconditional probabilities across heterogeneous consumers to obtain the market share for each alternative. Denote the vector of the consumer-specific parameters as θ_i and assume that it follows the distribution $P(\theta;\Omega)$, where Ω is the set of parameters 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, $\Phi_{pst} = \sum_r \phi_{pst}(r) * \gamma_r$, 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, I compute the search share for brand j by summing up the shares for the alternative with $s_j = 1$.

Finally, the model parameters – 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 web 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 non-linear least squares problem for the parameter estimation is given as:

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

4. Data

I apply my model to data from the U.S. video game console industry, specifically the seventh generation. This generation includes three main competing products: Nintendo Wii, Microsoft Xbox 360, and Sony PlayStation 3. Xbox 360 was released in November 2005, and the other two products were released in November 2006.

The data consist of two parts: the online search volume index and the sales of each brand. The sales data is acquired from VGChartz (http://www.vgchartz.com), which is a website that publishes sales estimates of video game consoles and software. For the web search volume, I use Google Trends data (http://www.google.com/trends/), which is a percentage of Google web searches for the terms that have been entered compared to the total number of Google searches done during that time. I assume that the total number of Google searches during each time period is constant, so that the Google Trends index indicates the web search volume. The provided index data is normalized so that the week with the largest percentage has the maximum index 100.

Both types of data are available weekly for worldwide regions from 2004, but I 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 2 and Figure 3 show the monthly observations of sales and web search volume, respectively.

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. I multiply a constant to the Google Trends data and then divide by the market size, to obtain the observed search share. The market size is defined as the number of the U.S. households in 2013 minus the total sales of Xbox 360 until October 2006.

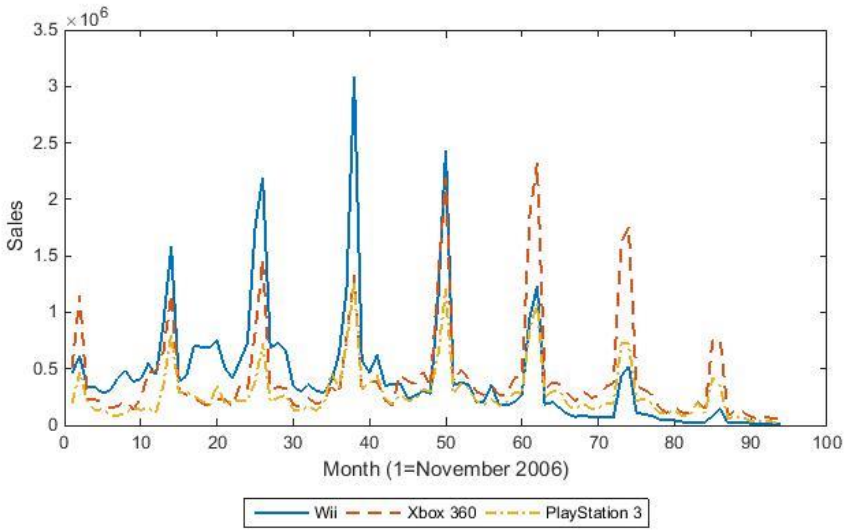
Table 1. Descriptive statistics

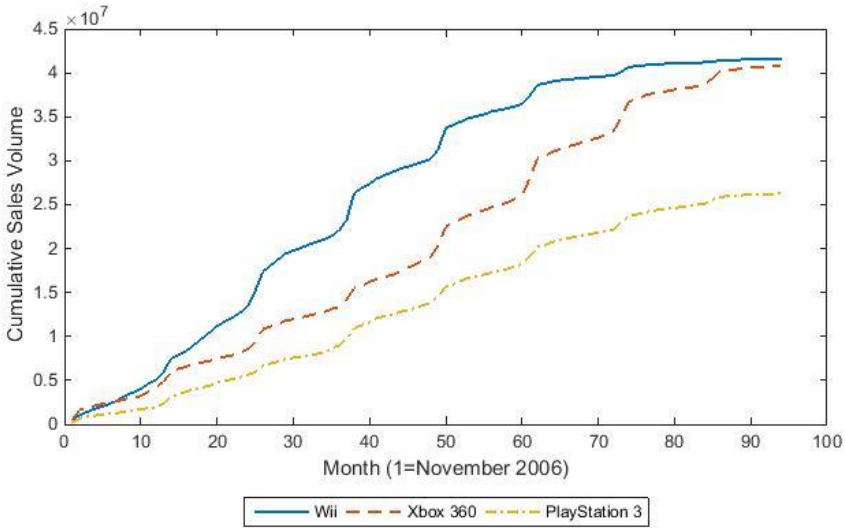
		Nintendo Wii	Microsoft Xbox 360	Sony PlayStation 3
Entry time		Nov 2006	Nov 2005	Nov 2006
Sales (units)	Total*	41,573,557	40,815,709	26,253,095
	Average	442,272	434,210	279,288
	Standard deviation	514,314	453,086	237,692
Web search (index**)	Total*	7,077.86	7,941.14	7,187.14
	Average	75.30	84.48	76.46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

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

** Google Trends index.

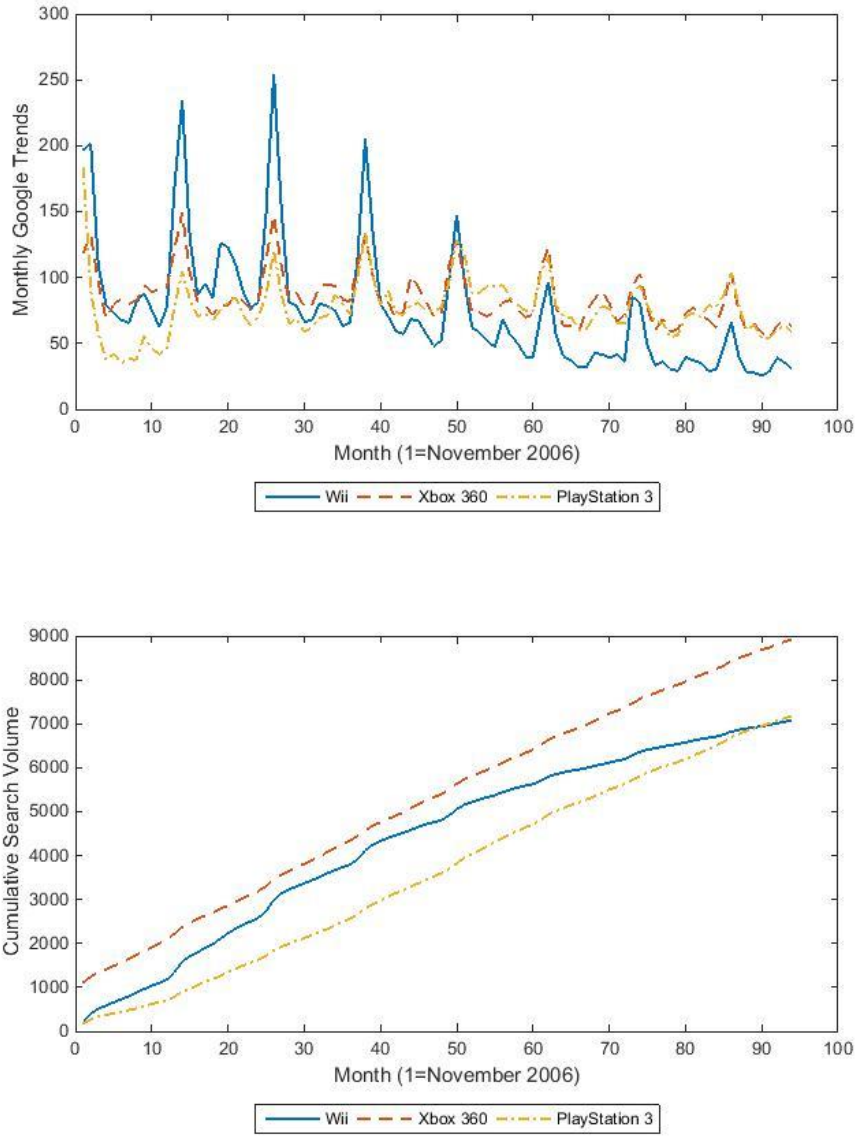
Figure 2. Sales volume of video game consoles





* Cumulative sales volume since November 2006

Figure 3. Web search volume of video game consoles



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

5. Empirical Analysis

5.1. Parameter Estimates

The estimated parameters are shown in Table 2. Using a latent class specification in order to account for consumer heterogeneity, I estimate four different models according to the number of segments assumed. For model selection, I conduct Wald tests with a null hypothesis that the parameters for segment r are identical to those for segment r′ in heterogeneous models. That is, the null hypothesis is $H0: \theta_r = \theta_{r'}$, where θ_r is the vector of the segment-specific parameters for segment r. The Wald test results are presented in Table 3. According to the four-segment model estimation results, the hypothesis that the parameters for segments 1 and 4 are identical and that the parameters for segments 3 and 4 are identical cannot be rejected. Hence, a three-segment model is found to be adequate for the data.

Consumers are classified into three segments with different intrinsic preferences for each brand, sensitivity to information from web search, and search cost. Consumers in segments 1 (36.09%) and 2 (23.73%) of the three-segment model are characterized as *search-reliant early purchasers*. They have a large parameter for the 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). In other words, they believe that the brand will eventually achieve a wide enough installed base, even in the initial stage where not much information about network size is available. This belief, along with their large search cost (c=2.1625 for segment 1 and c=2.6565 for segment 2),

leads to early purchase. In addition, because consumers in these segments evaluate the probability for large network size based on the information from search, they highly value a brand with large network size indicated by search. Hence, their brand choice highly relies on web search. 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 brand Wii, 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 regarded as *careful searchers*. In contrast to consumers in segments 1 and 2, consumers in segment 3 are less likely to show that the brand will eventually achieve a wide enough installed base (β=2.7852) and small search cost (c=1.6839). They delay purchase and continue the web search until the attained information is 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 the seasonality parameter for this segment is negative, but insignificant.

Table 2. Estimation results (Homogeneous model and two-segment model)

	Homogeneous Model	Two-segment Model Seg. 1	Two-segment Model 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	

Table 2. Estimation results (Three-segment model)

	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	

Table 2. Estimation results (Four-segment model)

	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

	H0	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

5.2. Policy Simulation

Based on the parameter estimates of the three-segment model, I conduct policy experiments and draw managerial implications related to keyword search advertising. Keyword search advertising has become an important research topic, because it is a dominant form of online advertising. Many papers including Edelman, Ostrovsky, and Schwarz (2007) and Varian (2007) focus on how the search advertising slots are sold via an auction mechanism. Several other papers have presented research based on keyword search advertising in connection with consumer search by constructing and using analytic models (Athey and Ellison 2011; Chen and He 2011; Desai, Shin, and Staelin 2014). Selecting keywords for search advertising is an interesting problem, but one that has been studied little (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, I 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, I assume that purchasing a competitor's brand name as a keyword affects consumers' consideration set. For example, a consumer who has only considered purchasing a Sony PlayStation 3 may search for Sony PlayStation 3, but be exposed to advertising for Xbox 360; then, they might begin to consider Xbox 360 as a candidate product. The impact of advertising on consumers' consideration set has been demonstrated by a number of papers including Yoo (2008) and Terui, Ban, and Allenby (2011).

The model presented in this paper 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. I assume that 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. 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 a different set A_s.

By comparing the sales and market share with those under keyword search advertising, I identify the effect 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. Table 4 shows the results for this policy simulation. Each row contains the firms' keyword purchasing decisions, the cumulative sales of each brand from November 2006 to July 2014, and the market share of each brand. The first row indicates the case without search advertising, and the results for the cases with search advertising are shown in the remaining rows. The arrows next to the numbers indicate the direction of change to facilitate comparison with the case in which there is no search advertising.

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%	(↑)

I find that 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 sales of the three brands in every case with search advertising is larger than the total sales in the case with no search advertising. It is possible that consumers accelerate purchases without switching brands. Hence, I analyze the impact of purchasing a competitor's brand name as a search advertising keyword on both sales and market shares.

When only one firm advertises (Table 4, Rows 2-10), the 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 mainly search for the keyword "Wii", some people may 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. Though consumers 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.

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%

Because of such a complex impact explained above, keyword search advertising does not always lead to the market share increase, especially 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 of Wii and Xbox 360 both increase, 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 show the case in which the sales of Xbox 360 decrease although Microsoft purchases a search advertising keyword because other firms – Nintendo and Sony – advertise aggressively.

From the analysis, I draw two managerial implications. First, when a firm purchases a competitor's brand name as a keyword, both the search volume of the keyword and the competition between the firm itself and the competitor should be considered. The large search volume of the keyword will lead to large exposure of the search advertisement, and the appropriate degree of competition will ensure that the exposure leads to purchase. If the competitor's brand far outstrips 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 consider other firms' strategies, such as which firms implement search advertising and which keywords they use. Drawing up a plan for keyword search advertising is not an easy task. This paper contributes to the literature by empirically quantifying the impact of keyword search advertising on sales and market share. However, questions about the

optimal keyword search advertising plan – such as when to implement search advertising and which keywords to purchase – still remain to be explored in future studies.

6. Conclusion

In this paper, an empirical model of web searching and purchasing behaviors was developed based on consumers' dynamic utility maximizing behavior, and the model was applied to the video game console industry. This study contributes to the marketing literature both theoretically and empirically. From the theoretical perspective, 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 an empirical 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 competition between the firm itself and the competitor should be considered. I also find that the impact of search advertising depends on the competing firms' search advertising strategies.

Despite the theoretical contributions and managerial implications, this study 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, 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.

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국 문 초 록

네트워크 효과가 있는 내구재 시장에서 소비자의 웹 검색과 구매 행동에 관한 연구

본 연구에서는 네트워크 효과가 있는 내구재 시장에서 소비자들의 웹 검색과 구매 행동을 설명하는 동태적 구조모형(dynamic structural model)을 개발하였다. 모형에서 소비자들은 구매 전 웹 검색을 통해 각 브랜드의 사용자 네트워크의 크기에 대한 기대를 형성하며, 그 기대를 바탕으로 언제 어떤 브랜드를 구매할 것인지 결정한다. 소비자들의 웹 검색과 구매에 관한 결정은 동태적 효용을 극대화하는 선택이다. 개발한 모형은 판매량과 웹 검색 횟수 데이터를 이용하여 미국 비디오 게임 콘솔 시장에 적용하였다. Nested Fixed Point 방법을 통해 각 브랜드에 대한 본질적 선호, 웹 검색으로부터 얻는 정보에 대한 민감도, 정보 탐색 비용과 관련된 모수들을 추정하였고, 이로부터 소비자들이 서로 다른 특성을 가지는 3개의 소비자 집단으로 분류될 수 있음을 확인하였다. 마지막으로 추정한 모형을 바탕으로 하는 policy simulation을 통해 경쟁자의 브랜드 이름을 키워드로 이용하는 검색광고의 효과를 알아보고, 이로부터 키워드 검색광고에 관한 경영 시사점을 도출하였다.

주요어: 소비자 정보 탐색; 신제품 도입; 네트워크 효과; 동태적 구조모형
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