Ph. D. Dissertation in Economics

The Influence of Internet Searches on Consumer Purchasing Decisions

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이 논문을 경제학박사학위 논문으로 제출함

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Abstract

The Influence of Internet Searches on Consumer Purchasing Decisions

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The purpose of this study is to examine the influence of the internet searches on consumer purchasing decisions for new products and services. To this end, this study considered the TV advertising effects on the consumer decision-making process in terms of awareness and preference, and then it examined the search query volume as the new consumer behavioral pattern. In this way, the study develops an integrated model to analyze various factors of the advertising effects. The proposed model analyze TV advertising sales effects along with changes in consumer behavioral patterns, specifically the consumer decision-making process, caused by exposure to TV advertising.

Empirical analysis is conducted by three econometric methods. Two of them are the "simultaneous equation model and path analysis". These methods address the endogeneity and causality relationship issues of various advertising measures. The other method is random utility model. This model deal with internet search query data as aggregate level of consumer demand. These models identify the major variables of the advertising effects in the consumer decision-making process. The estimation results proved that internet searches for product information influences purchase decisions, which marks a change in the consumer behavior pattern. Also, TV advertising and the search query volume are closely related. Examining each variable's effectiveness has strategic implications to maximize the advertising effects in the consumer decision-making process. This study showed that changes in consumer behavioral patterns should be considered in measuring advertising effectiveness. This approach could be a step toward understanding Internet searches' influence on consumers' purchase decisions. Finally, this study could be used to formulate companies' advertising strategies and government advertising regulations because consumers might base their purchasing decisions on Internet search results rather than TV advertisements.

Keywords: advertising, information search, consumer decision-making process, advertising measure, television

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Chapter 1. Introduction

1.1 Research Background

Advertising, a form of promotion, is one of the most influential factors in consumers' purchasing decisions. Because consumers desire more information about what they plan to buy, they refer to information sources such as TV advertisements, magazines, promotional websites, and so on. Marketing strategy involves advertising that encompasses various techniques, and an advertiser uses marketing strategies to communicate with current and potential customers. As shown in Figure 1, advertising has various purposes with regard to communication, including raising brand awareness and enhancing preferences, with the ultimate goal of increasing sales by stimulating consumers' purchasing needs (Sriram et al. 2010). Because advertisers want quantitative measures for effective advertising, advertising effects are measured by frequency of exposure, awareness, and preference, and advertisers target audiences via traditional mass media such as TV, radio, newspapers, and magazines (Naples and Michael, 1979; Whan Park, et al. 1988). Quantitative measures serve several purposes. First, advertisers want to know whether they meet their advertising goals. Second, firms must allocate advertising spend owing to budget constraints. Finally, advertisers want to evaluate their marketing strategies and modify them based on the budget allocation. Quantitative measures are used because sales are not always driven by the advertisements; moreover, the purpose of advertising has been diversified not only to increase sales but also to promote brand awareness and brand loyalty.

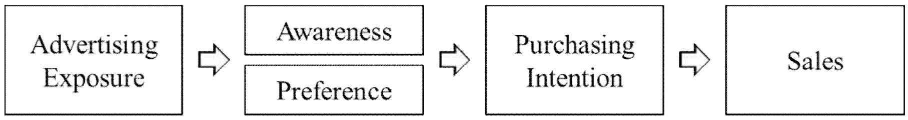


Figure 1. Conceptual flow of advertising effects

The introduction of new mobile devices and the ever-increasing influence of the Internet have changed the media environment, altering traditional advertising effects because consumers now use the Internet to supplement the information they receive via TV, radio, and other media (Ghose and Yang, 2009). In particular, the Internet keyword search for products and services exposed in TV advertising has drawn more attention (Zigmond and Stipp, 2010). Real-time popular keyword ranking provided by major Korean Internet portal services, such as Naver, Daum, Google Korea, and Yahoo Korea, showed that keyword searches related to TV figures ranked high. In fact, mobile devices make it easier to search TV figures in real time while consumers are watching TV. In addition to searching TV figures, consumers search products and services from TV advertising, which directly influenced consumers' purchasing decisions in the past. However, because Internet searches are now more common, consumers actively engage in gathering detailed product information on the Internet, using keyword searches rather than being satisfied by the information provided in the short TV commercials (Decker and Trusov, 2010; Ghose and Yang, 2009). As a result, the increasing volume of web search queries represents consumers' spontaneous response to TV advertising, and thus, the Internet keyword search should be taken into consideration as an effective measure, along with traditional advertising effect measures.

In Korea, TV is the highest advertising spending medium among traditional media, including radio, newspapers, and magazines. Since TV has evolved into a "smart TV," which integrates the PC and the television set/set-top boxes, not only TV manufacturers including Samsung but also ICT service providers such as Google and Apple compete in the market. The consumer behavior pattern of "searching the Internet while watching TV" is likely to be enhanced since smart TVs enable Internet searches while consumers watch TV, without any extra devices.

In addition to accelerating the use of PPL (product placement) as a new revenue source, this type of change in the consumer behavior pattern is also expected to fundamentally change the TV advertising ecosystem in determining advertising rates and measuring advertising effects. Moreover, for their purchasing decisions, consumers rely on Internet search results rather than on TV advertising, which reveals the limitations of the TV-focused advertising regulation policy. Therefore, it is necessary to conduct an empirical study on how web searches for product information influence consumers' decisions after they are exposed to TV advertisements.

1.2 Research Objectives

The Internet constitutes a convenient, accessible, and growing source of information for consumers. Consumers actively engage in the research of manufacturer product data through Internet searches and obtain additional third party information.

What kind of information does the consumer acquire through searching the Internet? In the past, the consumer simply accepted the product information provided by the company, and this was their primary information source. These days, however, a variety of product information is interactively provided not only by the company but also by other consumers. For example, before a product launch, companies disseminate product information through brochures, online banner advertising, blogs, and social media as well as teaser advertisements. Consumers also provide information through their product reviews aimed at potential customers. Web searches enable these consumers to access a variety of information provided by the company or by other consumers.

In Figure 2, consumers' web search data showed that query volume increases with the start of the marketing campaign, reaches its peak around the new product/service launch, and slows down while keeping steady when the sales are in full swing.

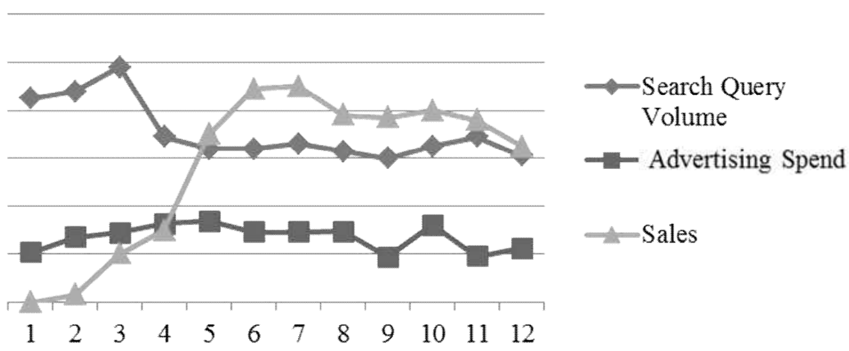


Figure 2. The relationship between advertising spend, sales, and search query volume of keyword “Anycall”

(Sources: Google trends, Samsung mobile, Korea CM Institute)

In other words, advertising influences the web search query volume and is likely to contribute to sales. The current matrix to measure advertisement effects, however, does not reflect the recent change in consumers’ purchasing decisions.

The consumer behavior pattern of “searching the Internet while watching TV” is likely to be very important change that would make existing TV commercial business model. Therefore, it is necessary to conduct an empirical study on how web searches for product information influence consumers’ decisions after they are exposed to TV advertisements.

Figure 3 presents the key concept of the proposed model in this dissertation. The model reflects recent consumer behavioral patterns following the effects of advertising.

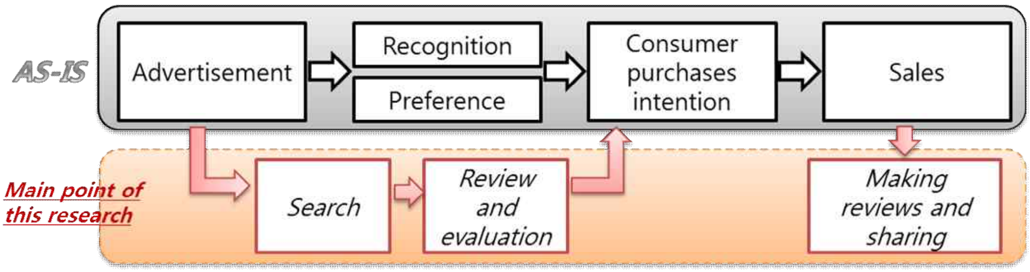


Figure 3. Conceptual framework of the advertising measure including the consumers' behavioral pattern

This dissertation's proposed model differs from the current matrix measure advertisement effects because it focuses on consumer research activity performed by Internet search, reviews, and evaluation. An analysis of the search query volume data provides information concerning the influence of the advertising effect following consumer exposure to new product TV advertisements.

The purpose of this study, then, is to examine the influence of the web search query volume as an advertising effect after consumers' exposure to TV advertisements on new products and services. This study considers the relationship between the consumer decision-making process and advertising effects. An analysis of this relationship suggests that recent consumer Internet search behavioral could be included in the advertising effects flows presented in Figure 4. I develop an integrated model to analyze the various factors of the advertising effect that reflect the consumer decision-making process and recent behavioral patterns. The model identifies the main variables of the advertising effects with respect to the consumer decision-making process. The examination of each variable's effectiveness has strategic implications concerning the advertising effects on the consumer decision-making process.

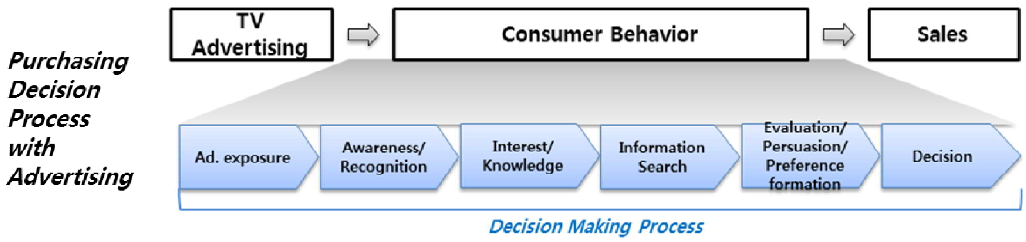


Figure 4. Conceptual Outline

1.3 Research Framework

In this dissertation, an integrated model is proposed that considers recent consumer behavioral patterns in the consumer decision-making process. The proposed model includes the existing matrix advertising factors such as communication and sales effects. This dissertation offers two perspectives that are presented in Figure 5. These perspectives integrate the new and current measures.

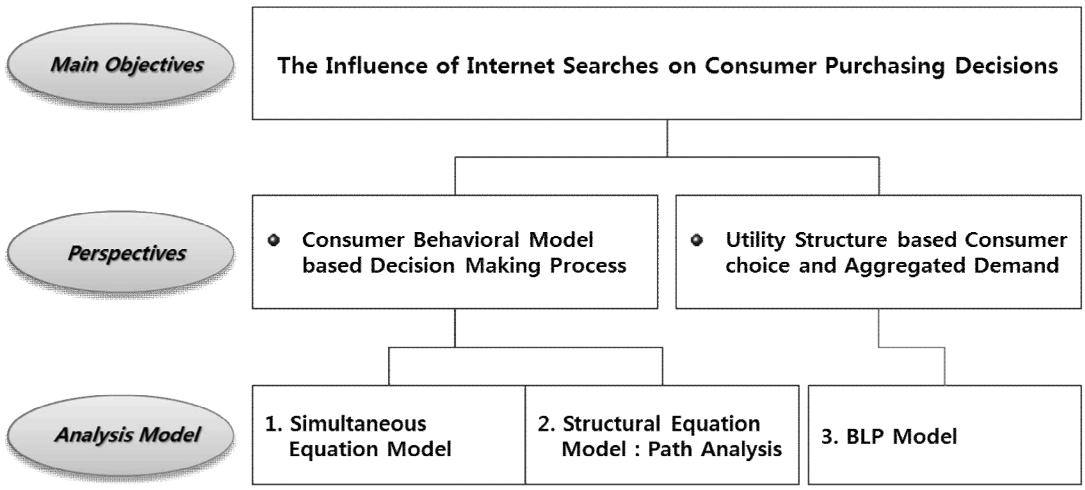


Figure 5. Framework

The first perspective pertains to the consumer decision-making process. Based on consumer behavior and customer psychology theories, I identify the significant advertising measures. The second perspective pertains to consumer choice theory based on utility structure. Consumer preference is exhibited in various ways. Internet searching represents spontaneous consumer awareness and preference and the search query volume data are one measure of consumer preference presented on an aggregate level. Therefore, this study uses the BLP (Berry, Levinsohn, Pakes) method to analyze consumer Internet searching patterns for product information. This method identifies the main variables of the product attributes with respect to the consumer decision, and the advertising, sales effects considering the web searching effect.

1.4 Outline of the Study

This paper is organized as follows: Chapter 2 presents theories on the traditional advertising effect measurements, consumer behavior patterns, and the limitations of previous studies. Chapter 3 provides a theoretical background of the advertising effect measurement that is proposed in the study, and examines the validity of estimation models that measure the integrated advertising effects. Chapter 4 conducts an empirical study by estimating the three proposed models concerning advertising and sales. Chapter 5 summarizes the result of this dissertation and states the implication and limitations of this research.

Chapter 2. Literature Reviews

2.1 Consumer Behavior in Decision Making Process

Consumers typically search for product information from various sources before concluding a purchase decision to optimize rational consumption. Many studies have investigated consumer behavioral patterns as consumers peruse information in order to find the right products that meet their needs.

Consumer behavior models based on behavioral science in marketing have been developed since the 1960s. Some of the best-known models are the Howard and Sheth Model; Blackwell, Miniard and Engel Model; and Battman Model (Blackwell et al., 2005).

Figure 6 presents a reconfiguration of the Blackwell, Miniard, and Engel model (2005). Various promotion strategies are incorporated in the model to analyze the effect of market stimulus in consumer behavior. Information processing is initiated by exposure to external stimuli. The purchasing decision-making process comprises seven steps: the recognition of the desire to purchase, the information search, the evaluation of alternatives, purchasing, consumption, post-purchase evaluation, and reaction. If pre-purchase activities are considered a problem-solving process, consumers evaluate the alternatives “in the search-for-information stage” to solve the problem. After information searching process, consumers have several alternatives, they evaluate the alternatives. The standards for evaluation are based on established consumer perception of the product. This perception, if positive, will eventually lead to a purchase. If the consumer is satisfied with the product in the post-purchasing evaluation step, the consumer perception of the product is intensified and can result in repeat purchases.

Therefore, if advertising is regarded as one of the channels in the information search, each stage of the consumer behavioral pattern to make a purchase is an important variable to measure the advertising effect. Moreover, the consumer decision-making process is not always applied equally to all products; rather, it mainly applies to situations in which the consumer has little information about the product, or the consumer anticipates a big loss, which usually pertains to products such as cars, home appliances, and furniture. Before purchasing, consumers tend to spend more time searching for additional information about the durability of goods such as cars and electronic devices because these products are used by the entire household, and they are relatively high priced considering consumers’ household incomes.

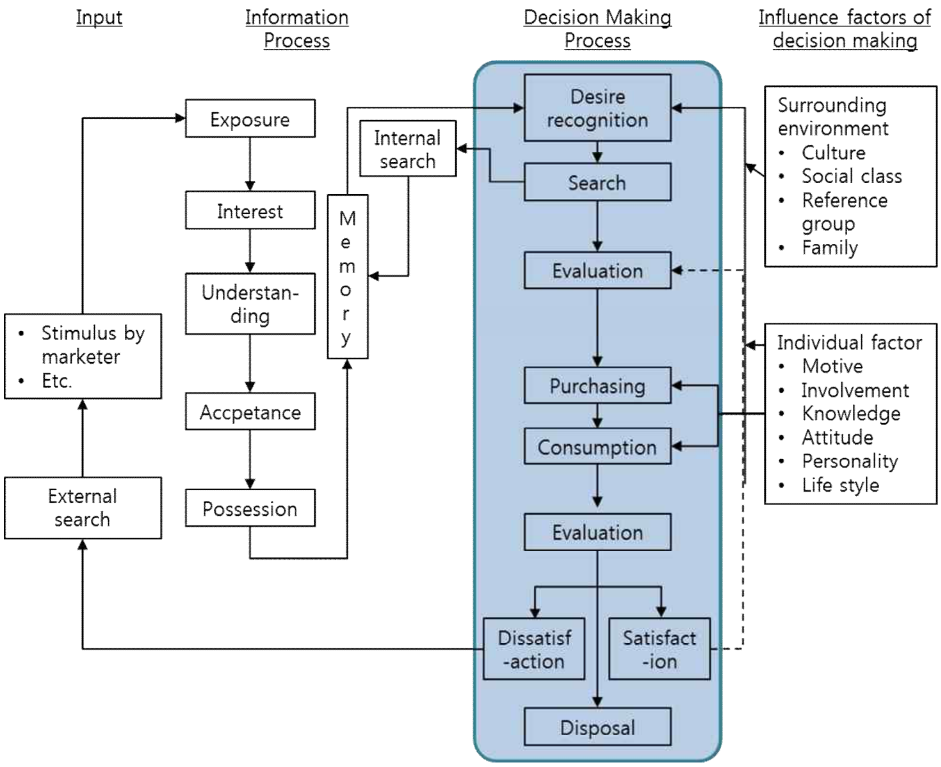


Figure 1. Consumer behavioral model

(source: reconfiguration of the Blackwell et al, 2005)

After obtaining detailed information, consumers visit the retail stores for a trial run or test drive. Otherwise, they rely on other consumers' product reviews as a crucial source of information in deciding whether to buy a product. Figure 7 presents several types of consumer decision-making processes that are based on the level of involvement such as habitual decision making, limited decision making, and extended decision making (Hawkins el al., 1983).

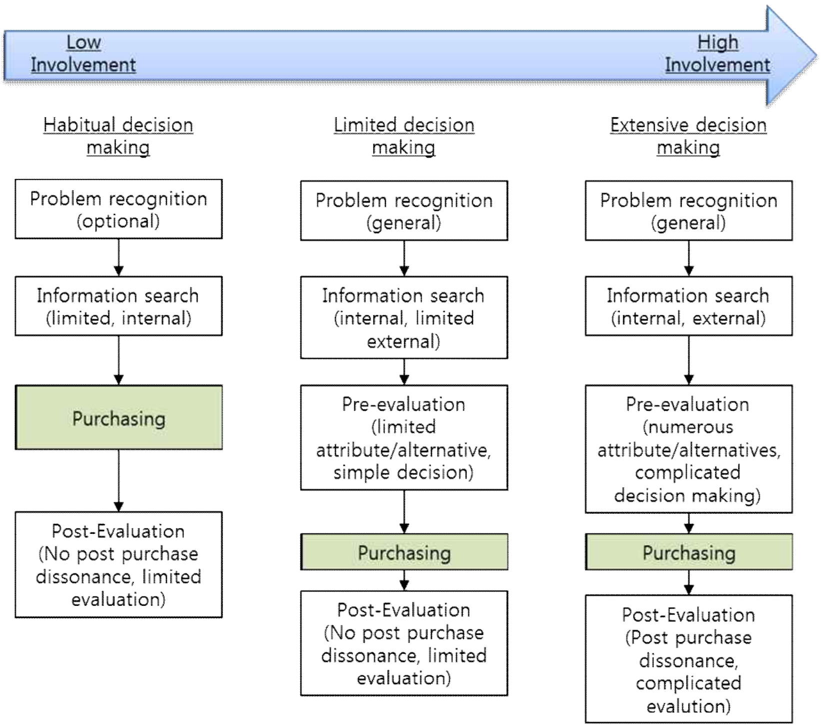


Figure 7. Decision making type and involvement level

(Source: Hawkins et al., 1983)

Extended decision making is applied when the consumer lacks product information or anticipates significant loss if the wrong decision is made. This type of decision making typically applies to high involvement products such as automobiles, home appliances, furniture, and clothes.

Figure 8 presents another decision-making model based on the Sternthal and Craig model. This model explains the internal processing of received information. The model suggests that when a consumer is exposed to information, the individual experiences sensory arousal, becomes more attentive, and initiates a cognitive analysis process. The process of cognitive analysis is related to the short- and long-term memory system of consumers (Yoon, 2002).

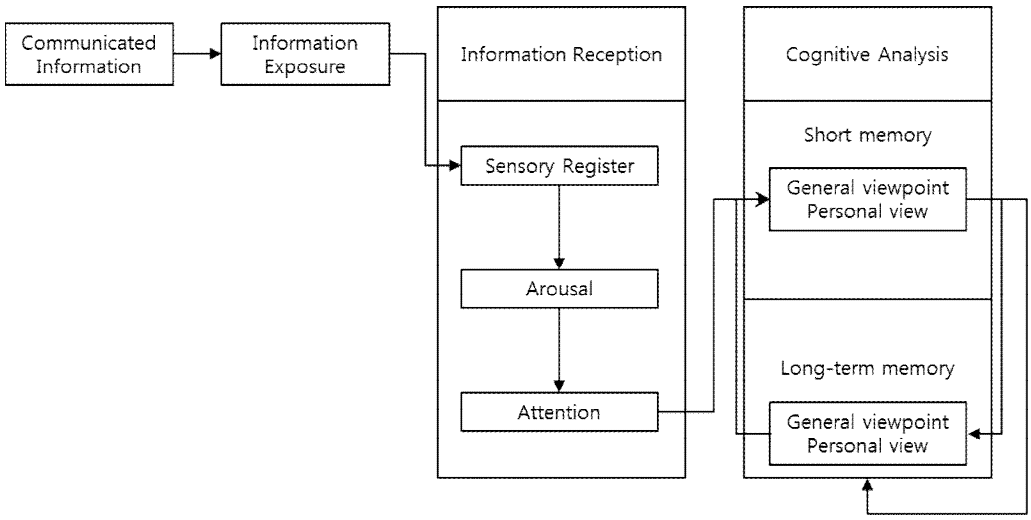
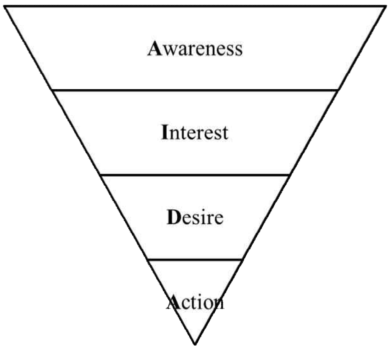


Figure 8. reconfiguration of Sternthal and Craig Model (Source: Steiger, 1990)

There are several models that classify consumer behavior patterns according to the advertising communication perspective. There are four representative models that are commonly referred to and implemented in the advertising industry. The first, the ADIMA model, is based on the cognitive learning theory that addresses information processing by individuals. This cognitive process is a step-by-step learning process. Figure 9 presents the AIDA (attention, interest, desire, and action) rule, from which the model is developed. Individuals follow the steps of AIDA in communicating a message (Lewis, 1898).



	AIDA model	**Hierarchy of effects model**
Cognitive stage	Attention	Awareness Knowledge
Affective stage	Interest	Liking Preference Conviction
Creative	Action	Purchase

Figure 9. AIDA model

(Source: provenmodels.com)

The AIDA rule was developed by E. St. Elmo Lewis in 1898, and the rule improved the AIDMA model by including the memory step between desire and action. The AIDMA model presented in Figure 10 is a respected theory that was suggested by Roland Hal in the context of advertising business practice. This model is the basis of the classical advertising acceptance behavior model and has significantly influenced marketers, whose goal is to achieve consumer acceptance of advertising. The AIDMA model is typically applied in conjunction with the FCB grid model.

The FCB grid model was suggested by Dave Berger and Richard Vaughn, from the advertising company Foote, Cone, & Belding, in 1980. The model separates consumer desire into cognitive and emotional desire and includes involvement level as a condition. Figure 11 presents the model. It features a two-by-two matrix that has four quadrants with two factors. The matrix suggests that the four categories are based on the involvement level with consumer information processing, which primarily requires thinking and feeling (Richard, 1986).

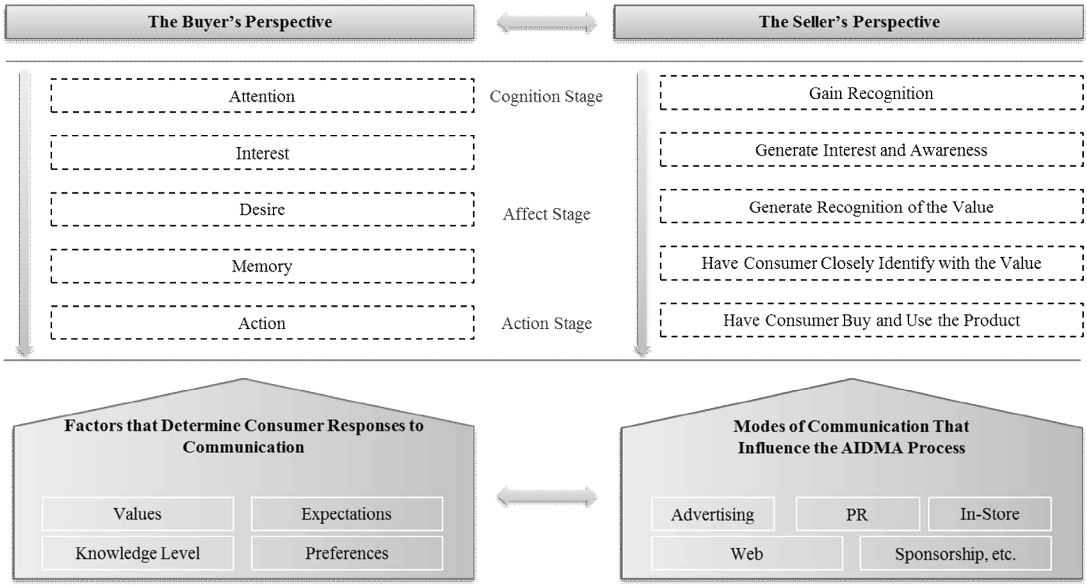


Figure 10. AIDMA model

(Source: http://www.mitsue.co.jp/english/case/marketing/02.html)

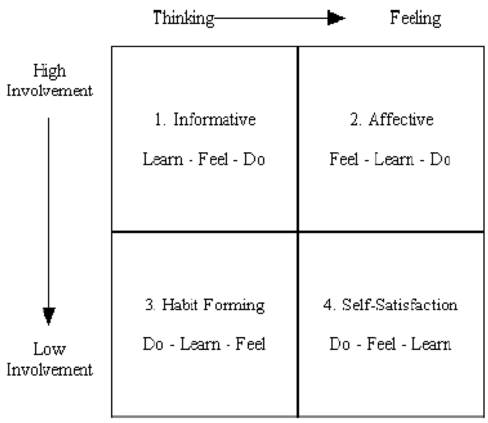


Figure 11. FCB model

(Source : Richard, 1986)

Table 1 presents the four categories of the FCB model. The first category implies that this type of product requires rational consideration prior to the consumer purchase decision. For example, disposable income could be a determining factor. Therefore, a consumer decision concerning these types of products requires additional detailed product information, which is typically obtained from an Internet search.

Table 1. FCB grid model

	Think	**Feel**
High involvement	**1.Informative** car, house, furniture Learn – Feel - Do	**2. Affective** jewelry, cosmetic, fashion Feel – Learn – Do
Low involvement	**3. Habit Formation** grocery, home appliance Do – Learn - Feel	**4. Self-satisfaction** cigarette, alcohol, snack Do – Feel - Learn

Consumer behavior based on cognitive learning follows a learn-feel-do process. Therefore, effective advertising should stimulate consumer interest and provide a motive to purchase. This model offers the strategic perspective that the central message of an advertisement should depend on the market positioning of the product. However, this model is limited because every consumer does not necessarily complete the learn-feel-do process. The three steps could be re-arranged to learn-do-feel, or even do-feel-learn, to address the sequence of information processing, depending on the product type.

The AIDCA (attention, interest, desire, conviction, and action) model is suggested in business practice and is similar to the AIDMA model. This model differs from the AIDMA model because a memory step is substituted for conviction. The AIDCA model is based on cognitive dissonance theory. Customers rely on advertising to provide information for a purchasing decision. If a consumer fails to satisfy their purchasing need, they experience cognitive dissonance with respect to the lack of action. Therefore, an advertiser may conduct complementary advertising to ensure repeat purchasing and brand loyalty from consumers.

Figure 12 presents a summary of the various models from the perspective of advertising communication in business practice.

Historically, communication between consumers and firms has been one-directional, and consumers have been passive information recipients (Hoffman & Novak, 1996). However, consumers now actively search for product information using the Internet.

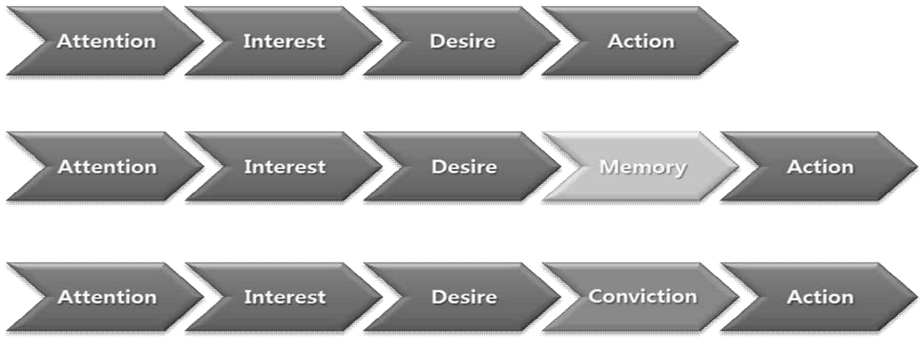


Figure 12. Various models as advertising communication perspectives in business

A model that reflects this consumer trend, the AISAS(attention, interest, search, action, and share), has been suggested by the renowned Japanese advertising company, the Dentsu Group. The major difference between the AIDMA and the AISAS model is that desire is substituted for search and information sharing following the purchase. The purchase is a new action and is reflected in Figure 13.

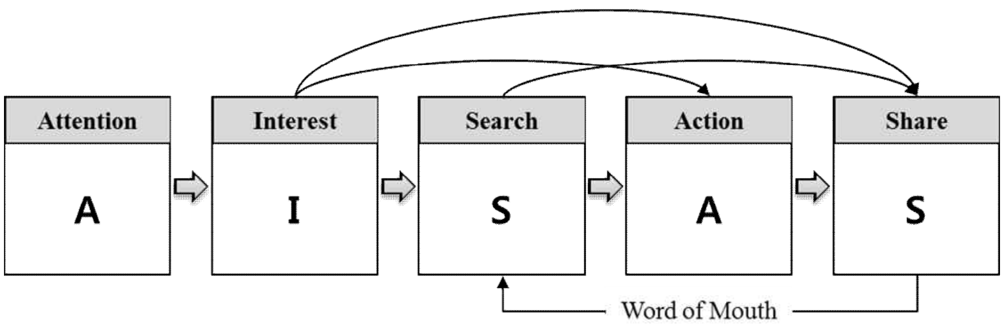


Figure 13. Online consumer behavior model by Dentsu Group

(Source : http://www.dentsu.com/crossswitch/crossmedia2.html)

This model was originally applied to online advertising and could also be applied to offline advertising analysis that includes general consumer purchasing decisions.

Rogers (2003) suggests another consumer behavior theory perspective with the innovation adoption model that consists of five steps: awareness, interest, evaluation, trial, and adoption (Rogers, 2003). This model is based on the innovation diffusion process and is presented in Figure 14. The model categorizes consumer behavior into three steps, communication, decision, and assessment for the whole innovation process.

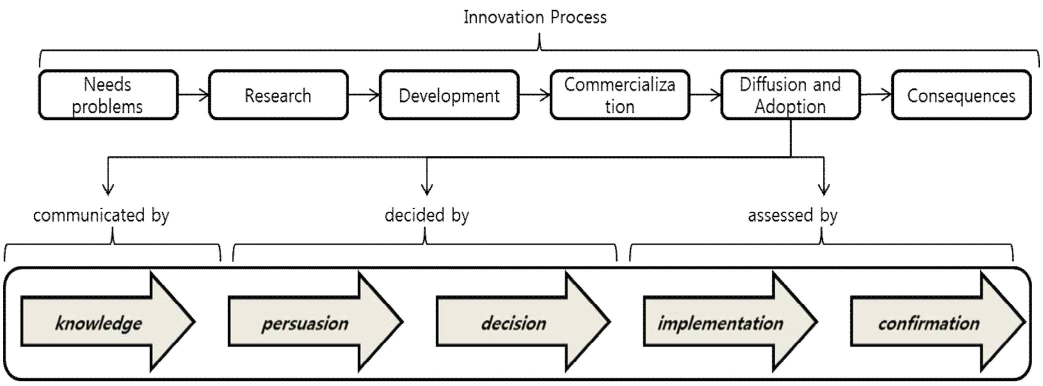


Figure 14. The flow of consumer behavior according to the innovation diffusion process

(Source : rearranged the Rogers, 2003)

These three steps are similar to the steps in the general consumer decision-making theory: knowledge, persuasion, decision.

A report by the Korea Chamber of Commerce and Industry, “Changes in consumer behavior following price inflation.” defines a change in consumer patterns as the sale, the purchasing of a small amount, a preference for a low price, and brand transfer, and is abbreviated as SALT. Internet stores are among the most frequented retail outlets (48.5 percent). Additionally, 43.5 percent of households who use both online and offline stores state that they purchase products after researching the product on the Internet. Another 23.5 percent state that they purchase from Internet malls after visiting offline stores. The recent consumer trend, SALT, creates additional demand for low-price products and empowers retail channels (Korea Chamber of Commerce and Industry, 2012).

2.2 Advertising-Sales Response

Advertising, a form of promotion, is one of the most influential factors in consumers' purchasing decisions. Marketing strategy involves advertising that encompasses various techniques, and an advertiser use marketing strategies to communicate with current and potential customers. Firms allocate advertising spend owing to budget constraints. Most of the selling and administrative expenses are the advertising spend even though it depends on the type of product or firms' marketing strategies. In Korea, the pharmaceutical industry typically does execute many advertising on a large scale. They use advertising spend thirty-four point five percent of the total sales on average in case of KOSPI listed company, thirty-five percent of the total sales on average in case of KOSDAQ listed company, and even maximum fifty percent of the total sales according to circumstances.[1]

Therefore, measuring advertising quantitatively is significant. Quantitative measures serve several purposes. First, advertisers must determine whether they are meeting their advertising goals. Second, firms must manage budgets and advertising expenses. Finally, advertisers must evaluate their marketing strategies and modify them based on budget

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[1] The Financial supervisory service, 2012 3rd quarter, based on the listed pharmaceutical company ranking top 30

allocations. Quantitative measures are used because sales are not always driven by advertisements. Moreover, the purpose of advertising has been diversified to increase sales and to promote brand awareness and brand loyalty.

The advertising effects include “communication effects” and “sales effects.” Based on the consumer behavioral theory, the communication effects study measures consumers’ attitude change following exposure to an advertisement at an individual level. Regarding this type of study, which began in the 1950s, Cohen (1987) suggested that consumers’ response to advertising varied, depending on the advertising method and consumers’ circumstances (Cohen, 1987).

The advertising impact on the consumer’s decision-making process has been the focus of a number of studies. Vakrastsas and Amber (1999) reviewed over 250 papers and summarized their findings based on seven major categories as follows (Vakratsas & Ambler, 1999).

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(i) Market response model

(ii) Persuasive hierarchy model (think - feel – do)

(iii) Low involvement hierarchy model (think – do – feel)

(iv) Integrated models

(v) Cognitive information models

(vi) Pure affect model

(vii) Hierarchy free models

According to their paper, advertising message, advertising channel, and frequency are filtered by advertising purpose and product involvement. Consumers form an attitude toward the advertisement after exposure to it, and their attitude influences their decision making. Horsky and Simon (1983) found that advertising played a role as an early source of information to innovators by informing them of the existence of the new product, as these innovators adopt the product and affect the imitators by word-of-mouth (Horsky & Simon, 1983). Assael (2004), who also studied the effects of word-of-mouth, demonstrated that word-of-mouth is more important in a brand new product when the consumer has not developed any specific attitude toward it (Assael, 2004). Henning-Thruar et al. (2004) defined electronic-word of mouth (e-WoM) as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Henning-Thruar, 2004). Duan et al. (2008) consider online reviews both influencing and influenced by movie sales. The consideration of the endogenous nature of online user reviews significantly changes the analysis (Duan, Gu, & Whinston, 2008). Whan Park et al. (1988) developed a framework in which advertising is conceptualized as having multiple effects based on the decision-making process "Awareness – Interest – Evaluation – Purchasing - Repeat purchasing." In this article, although advertising directly impacts brand awareness and attitude as a direct communication effect, it does not greatly influence consumers' preference formation and evaluation. Based on these results, I should be mindful of recent consumers' behavioral changes (e.g., price comparisons and searches for product details) as an advertising effects measure (Whan Park et al, 1988).

Advertising sales effects differ from advertising communication effects. The advertising sales effects are typically analyzed using econometric time series data to identify the sales response function. Conventionally, the relationship between advertising and sales, or market share, is a causal one. If advertising expenditure increases, sales increase, and vice versa. This theory is reasonable from a long-term perspective; however, previous literature has suggested that this might not be the case in the short term (Haley, 1978). For example, the sales response to an increase in advertising expenditure causes is an increase in sales. However, a temporary increase in sales levels will eventually decrease even if the increased advertising expenditure is maintained. Therefore, the relationship between advertising and the sales response presents a dilemma. The sales response to advertising differs according to the product type and the industrial sector. Hence, the analysis of the sales response is significant because it has implications for the development of an effective strategy (Park, Kwon, Yang, & Song, 2005).

The representative view of advertising sales response effects is measuring the sales and profit results of advertising (MESPRO) theory by Campbell (1969), who claimed that the effects of advertising should be based on the following question: “How much sales occur as a result of?” since the ultimate purpose of advertising is sales (Campbell, 1969; Gable, Harris, Fairhurst, & Dickinson, 2000).

The advertising sales response models are classified by Lilien et al. (1992) into the sales response model and market share model (Lilien, Kotler, & Moorthy, 1992). No consistent conclusions have been drawn about which dependent variables are more effective. The market share model is beneficial because it considers market competition when measuring advertising effects. When selecting the independent variables in the model, some studies use direct advertising measures, such as advertising spending, advertising share, and GRP (gross rating point), while others use another variable (except advertising measures).

Koyck (1954) suggests the distributed lag model. Certain studies use (t-1) period sales data as independent variables using the Koyck model (Koyck, 1954). The Koyck model is an outstanding model for goodness of fit (R2), and prediction capability. However, if the purpose of the analysis is to determine the net effects of advertising, caution is required in the results evaluation because of the possibility of overestimation.

Assumes et al. (1984) pointed out that advertising sales effects might differ based on the type of variables, data, product diversity, product life cycle, and estimation method, which makes it very difficult to generalize the advertising sales response effects (Assmus, Farley, & Lehmann, 1984).

The main purpose of advertising sales response model analysis is to determine factors such as elasticity and carry-over effect. The elasticity of advertising usually decreases in the long-term even though it is dependent on the product type. Additionally, the carry-over effects gradually decrease over time. Table 2 presents the relationship between elasticity of advertisement and the carry-over effects.

Table 2. Advertising elasticity, carry over effects

Purpose	Result	Researcher

Short term effect of advertising elastisity	0 ~ 0.2	Assmus et al.(1984) Leone and Schulz(1980), Lodish et al.(1995)
	Durable goods > Nondurable goods	Leone and Schultz(1980) Sethuranman and Tellis(1991)
The dynamic effect of dynamic advertising elasticity	Advertising elasticity decreased according to the PLC (Product Life Cycle). Therefore, the elasticity of new product is higher than existing product in market	Arora, 1997; Lodish et al.(1995) McDonald(1992)
The carry over effect	The effect of liking brand is higher than carry over effect	Givon and Horsky(1990)
	90 percent of the total advertising effect is disappeared after 3~15 months	Clake(1976), Leon(1995)

Another time series model that analyzes advertising sales responses is the multivariate time series model (Dekimpe & Hanssens, 2000). This model is used for three reasons.

First, the stability of marketing and performance variables influence the selection analysis model and, consequently, provide a measure with which to diagnose long-term marketing strategy. Second, variables are significant with respect to the identification of causal relationships in marketing and performance because the direction and magnitude of the time lag of the causality are central to time-series analysis. Finally, identifying linearity with unstable variables and long run equilibrium is required.

Table 3. Traditional time-series techniques in marketing

Study	Application area
Aaker et al. (1982)	Qualification of the sales-advertising dynamics when feedback relationships are present
Bass and Pilon (1980)	Are market shares in a long-run equilibrium that is temporarily disturbed by marketing activities?
Carpenter et al. (1988)	Inclusion of dynamically-weighted attraction variables in market-share models.
Didow and Franke (1984)	Reliability and validity assessment in a time-series context
Doyle and Saunders (1985)	The use of lead effects to capture the anticipations of consumers and other economic agents
Doyle and Saunders (1990)	Transfer-function analysis to infer the dynamic impact of advertising campaigns

Franses (1991)	Adding exogenous variables to the Autoregressive Moving-Average specification of a dependent performance variable
Geurts and Ibrahim (1975)	Comparison of the univariate forecasting performance of Box-Jenkins and exponential smoothing
Hanssens (1980)	Granger causality testing to identify competitive reaction patterns
Helmer and Johansson (1977)	Transfer-function analysis to model the dynamic impact of advertising on slaes
Jacobson and Nicosia (1981)	Evaluation of the causal relationship between macro-advertising and aggregate consumption
Kapoor et al. (1981)	Both deterministic and stochastic components are needed to model sales with pronounced, non-homogeneous seasonal patterns
Krishnamurthi et al (1986)	Using intervention analysis to assess the build-up effect of advertising in a field-experimental setting
Leeflang and Witting (1992)	The use of Granger-causality tests to reduce the information set in scanner environments
Leone (1983)	Transfer-function analysis to quantify the over-time impact of own and competitive advertising on sales performance
Moriarty (1985)	Decomposition of forecasting bias and development of a composite forecasting model from individual forecasts
Moriarty (1990)	The use of boundary value models to combine forecasts

Moriarty and Adams (1979)	Tests for a common structure in time-series models fitted to multiple brands, territories
Moriarty and Adams (1984)	Combining management judgement forecasts with econometric and time-series forecasts
Moriarty and Salamon (1980)	The use of seemingly unrelated time-series model to improve on the performance of univariate forecasting models
Roy et al. (1994)	Granger-causality testing to identify leader-follower behavior in price setting
Umashankar and Leodolter (1983)	How to improve the forecasting performance of univariate models by accounting for the contemporaneous correlations across the series
Wichern and Jones (1977)	Intervention analysis to quantify the over-time impact on market share of a discrete event

(Source : Dekipme & Hanssens 2000)

The market response model addresses consumer behavioral response to advertising, product price, and promotion, and considers factors such as the market share of the product and consumer brand preference. This model considers simple relationships concerning firm marketing activity and consumer behavior and excludes the communication effects. The relationship between advertising and sales is determined by various direct and indirect factors. The indirect factors include product attributes, consumer characteristics, the intensity of market competition, and the firm marketing strategy. The direct factors, which directly influence product sales, include the advertising goals, the amount of advertising, the commercial copy, the advertising medium, and the advertising scheduling.

In previous literature about the advertising sales response, many studies showed the elasticity of advertising sales and sales response functions. However, each study suggests a different sales response function depending on the product type, market positioning, intensity of competition, and so on. An econometric analysis of advertising effects, as above, might be effective in quantitative analysis, but this does not take into account the preceding factors such as consumers' awareness and brand attitude at an individual level. Therefore, it was difficult to discuss the preceding factors of sales because of the simple conclusion drawn: if a firm spent more on advertising, then sales would increase.

To summarize previous literature, advertising sales response effects models only verify the relationship with advertising and sales factors by econometric methods using time-series data. These studies use direct measures related to the advertising spend, such as advertising shares, GRP (gross rating point), and so on, as independent variables, and sales and market shares as dependent variables, and they examine advertising's contribution to sales by suggesting econometric models and empirical analyses.

Moreover, each study suggests a different response function depending on product positioning and the intensity of market competition. The econometric models and empirical analyses in advertising might be effective in quantitative analysis; however, the analyses are limited and do not consider communication effects on individual consumer levels such as awareness, emotion, and attitude, which are significant factors involved in the purchasing decision. Therefore, the analyses suggest only that increased advertising leads to an increase in sales or market share. It is impossible to analyze the preceding variable of sales.

2.3 Advertising and Consumer Behavior

Advertising often includes a substantial amount of succinctly packaged information concerning the product. Advertisements during commercial breaks typically last between 15 seconds to one minute. It is impossible to inform consumers of detailed product information in such a small amount of time. Therefore, consumers perform searches independently. Historically, consumers would seek additional information by visiting retail stores for a trial run or to test the product. Alternatively, they would rely on consumer product reviews as a crucial source of information for purchase decisions.

With the widespread adoption of Internet search services, searching product information on the Internet while watching television is a new, emerging consumer behavior pattern, which changes firms' advertising strategies. Calder and Malthouse (2005) demonstrated how to improve media engagement on effectiveness when the advertising spending has been assigned to various media. BIGresearch has administered "the Simultaneous Media usage Survey (SIMM)" since the late 1990s (http://www.bigresearch.com). According to the 2006 research results, 67.9 percent of consumers used both television and another medium simultaneously. Therefore, BIGresearch suggests that advertising effects measures and media mix strategies should be changed based on consumers' simultaneous media usage patterns (BIGresearch, 2006). Wilson (2008) claimed that technology development enables consumers to media multitask (Wilson, 2008). With the widespread multimedia usage, many studies about cross-advertising effects have been conducted. Chang and Thorson (2004) claimed that the integrated advertising of the TV and web leads to more attention, more perceived messages, higher credibility, and a greater number of total and positive thoughts than did repetition by each medium (Chang & Thorson, 2004). Zigmond and Stipp (2010) also examined consumer behavioral changes by introducing a new metric—a measure of changes in Google search queries—and showed how television commercials initiate Internet searches by consumers. During world events, such as the Beijing Olympics 2008 and the Vancouver Winter Olympics 2010, the query volume of specific advertising spiked following the commercial as shown in Figure 15-16. They asserted that the effectiveness measure for TV advertising should introduce a new method based on "multi-platform media use patterns" (Zigmond & Stipp, 2010).

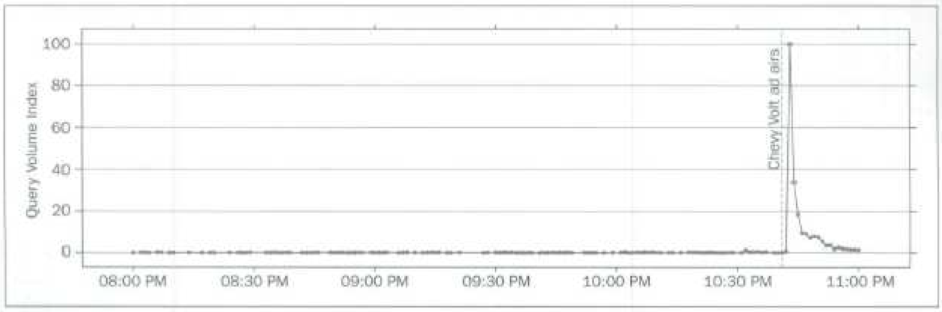

Figure 15. Search queries for “Chevy Volt” during Beijing Opening Ceremonies

(Source : Zigmong & Stipp, 2010)

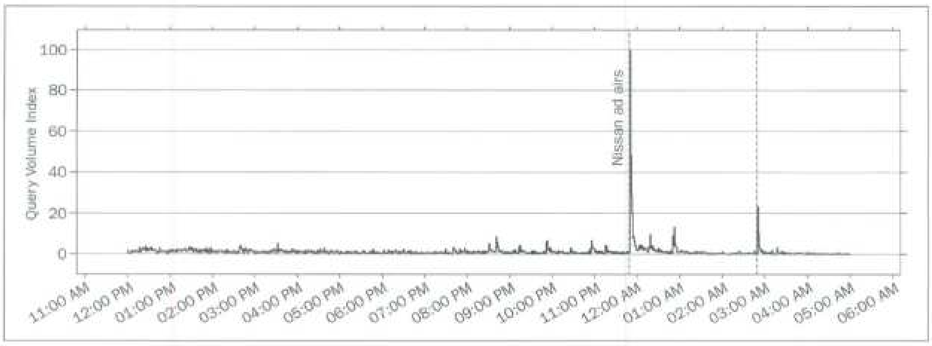

Figure 16. Search queries containing “Nissan Leaf” during Vancouver Opening Ceremonies

(Source : Zigmong & Stipp, 2010)

New media use patterns challenge researchers to identify measures of advertising effectiveness that capture these new usage behaviors. Further, supporting consumers' Internet searches plays an important role in their purchasing decisions. However, such research possesses limitations because it uses search query volume as the single direct measure of TV advertising and does not include the complete spectrum of advertising sales effects.

Nilsen, a worldwide market research company, reported in 2011 that more consumers were searching using smartphones, tablet PCs, and while watching TV as a result of increasing mobile Internet accessibility, see Figures 17 and 18.

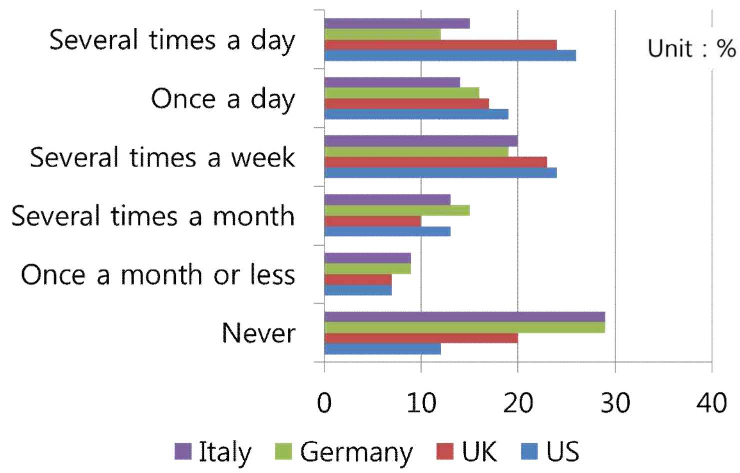

Figure 17. Simultaneous use of tablet while watching TV

(Source : Nielsen)

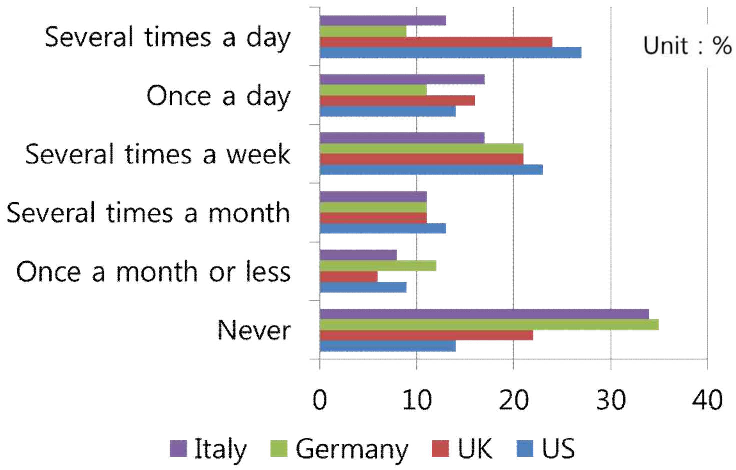

Figure 18. Simultaneous use of smartphone while watching TV (Source : Nielsen)

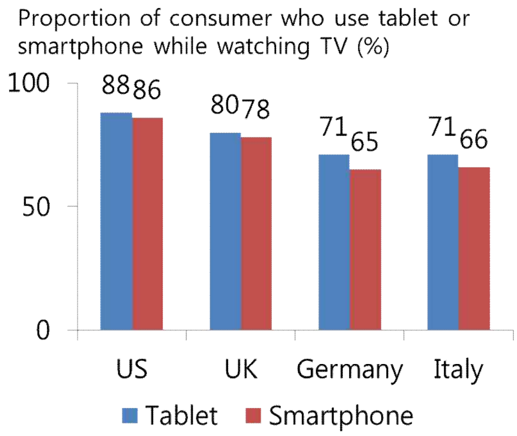

Figure 19. Double vision-global trends in tablet and smartphone use while watching TV, 4th quarter in 2011 (Source : Nielsen)

Juniper Research, the worldwide mobile research specialists, reports that the number of smartphone users who stream mobile TV to their devices could reach 240 million people by 2014 (Miller, 2012). Juniper Research reports “this increase will be driven by a rise in smartphone penetration and a growth in the usage of Internet TV and IPTV services.”

Gartner, a market research company, reports that the smartphone penetration rate represents 30 percent of the world’s population. The report predicts that tablet PC users who stream mobile TV to their devices will increase, and the average amount of TV watching time will reach 186 minutes per individual per month (http://www.dt.co.kr/contents.html?article_no=2012061302010831759002).

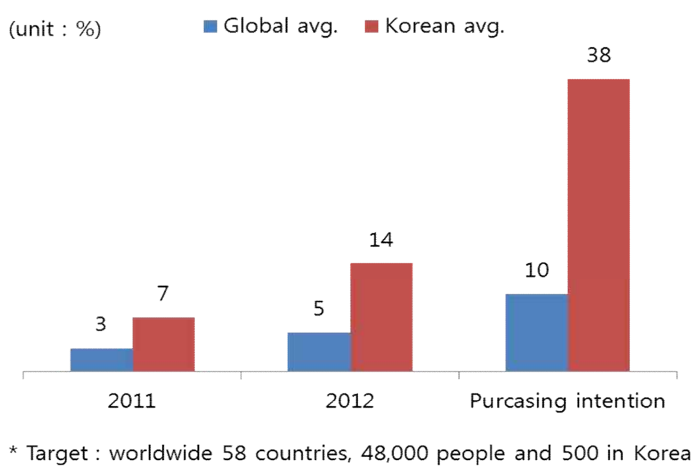

Figure 20. Possession and purchasing intention within 6 months for tablet PC

(Source: TNS)

The number of tablet PC users in Korea has doubled in the last year. Figure 20 illustrates the study, "Mobile life 2012 Korea," from the annual mobile life study by TNS (total national statistics). From a total of 500 respondents, 14 percent use tablet PCs compared to only 7 percent in the previous year. The percentage of future purchase intention with respect to the domestic tablet PC market is predicted to reach 30 percent. The increasing use of smartphones and the rising penetration levels of tablet PCs reflect a corresponding increase in consumer Internet search behavior for product information

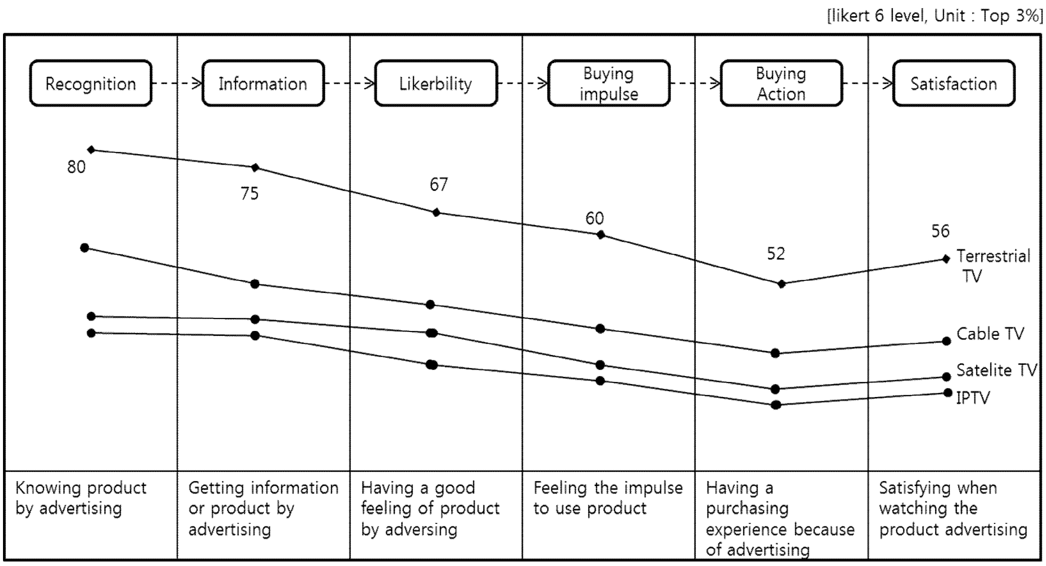

Figure 21. The effects of broadcasting media on purchasing process

(Source : rearranged KOBACO 2010 MCR report)

A comparative study of advertising mediums by KOBACO, presented in Figure 21, shows that terrestrial TV is the most effective advertising medium in terms of consumer concentration, likability, trust, and memory.

Additionally, early adopters who influence other consumers represent the group most affected by terrestrial TV commercial and Internet advertising. This implies that terrestrial TV commercials influence initial shoppers. Moreover, the product reviews by these early adopters indirectly influence potential consumers who may consider a purchase (Korea Broadvast Advertising Corporation, 2010).

Spalter (1995) suggests that the 7Is represent interconnection, interface, interactivity, involvement, information, individualism, and integrity in response to the conventional marketing mix of the 4Ps, which are the product, price, place, and promotion. The information contained in the 7Is is the result of powerful web search engines that offer extensive Internet services (Spalter, 1995).

Consumers focus on products before and after they have purchased them. Mills (1965) claimed that consumers prefer product advertising following a purchase. A previous study by Engle (1963) suggested that an individual who possesses a product pays more attention to the advertising of that product than an individual who does not possess the product (Mills, 1965).

The consumers who are exposed to advertising post purchase are influenced differently than the consumer who is exposed to advertising pre-purchase. Consumers evaluate their purchasing positively through post-purchase information searches. Additionally, consumers may advise others. These behaviors represent the word-of-mouth effect. From a diffusion process perspective, consumers who have not purchased a brand new product by a certain time following product launch may lack product information or a sense of value with respect to the product (Horsky & Simon, 1983).

For potential consumers, information sources are categorized into two types. The first category is advertising or the marketing strategy of the firm. The second category is the word-of-mouth effect from early adopters. Durable goods are not typically repeat purchases for individuals, and the word-of-mouth effect has substantial influence on the purchase decision. The follower group that waits to purchase requires experience or information from online advertising or an offline store trial.

To summarize previous literature about advertising and consumer behavior patterns, traditional advertising measures based on recall or recognition effectiveness did not properly assess the impact of advertising on consumers' behavior changes. The recent trend of consumer Internet search behavior might be a significant measure of advertising; however, limited studies have analyzed this recent consumer trend.

2.4 Limitations of Previous Literatures and Significance of the Study

The previous literature concerning advertising effects separates the performance measure into individual sales effects and communication effects.

First, the communication effect models based on consumer behavior analyzed only the decision-making process and not sales effects. The models that examine individual consumer awareness and attitude are ineffective because the models do not verify the advertising impact on sales or market share. Moreover, the relationships between recall and persuasion, or brand attitude and behavior, are not obvious. It is unclear whether advertising influences awareness and emotion is unclear. Therefore, it is impossible to determine the factors that could be variable as a link to sales effects. Additionally, the communication effect models use cross-sectional data that are obtained through consumer interviews using controlling exogenous variables. Hence, it is difficult to generalize the results.

Moreover, while a few studies analyzed the new trend of consumers' Internet searches, a major limitation is that those studies examined only the search query volume as the consumers' response to television advertising rather than considering the comprehensive effects, including sales effects.

Second, the advertising sales response effect models mainly address advertising elasticity, the duration of advertising, and the sales response functions using econometric methods. These studies use direct measures related to advertising expenditure and the results are dependent on factors such as the product type, market positioning, and the intensity of competition. An econometric analysis of advertising effects, as above, might be effective in quantitative analysis, but this does not take into account the preceding factors such as consumers' awareness and brand attitude at an individual level.

Therefore, it was difficult to discuss the preceding factors of sales because of the simple conclusion drawn: if a firm spent more on advertising, then sales would increase.

Tellis (1997) suggests that the methods used in conventional advertising effect analysis are separated into experimental approaches and field approaches. An experimental approach is conducted under hypothetical circumstances by controlling the variable and is an effective method to identify causal relationships. However, it is hard to replicate a real situation. A field approach is based on real data that reflect reality but are impossible to control. Therefore, the field approach has limitations in identifying causal relationships (Tellis, 1997). Because these two methods possess advantages and disadvantages, Tellis (1997) suggests that an integrated study that exploits the advantages of each model is required.

The previous literature focused on the relationship of advertising with consumer response and advertising with sales. The research has suggested a model to identify these relationships and for empirical testing.

The existing models are insufficient to consider both relationships comprehensively. There is no model that integrates the aggregated market level advertising effects with levels of individual consumer behavior as shown in Figure 22.

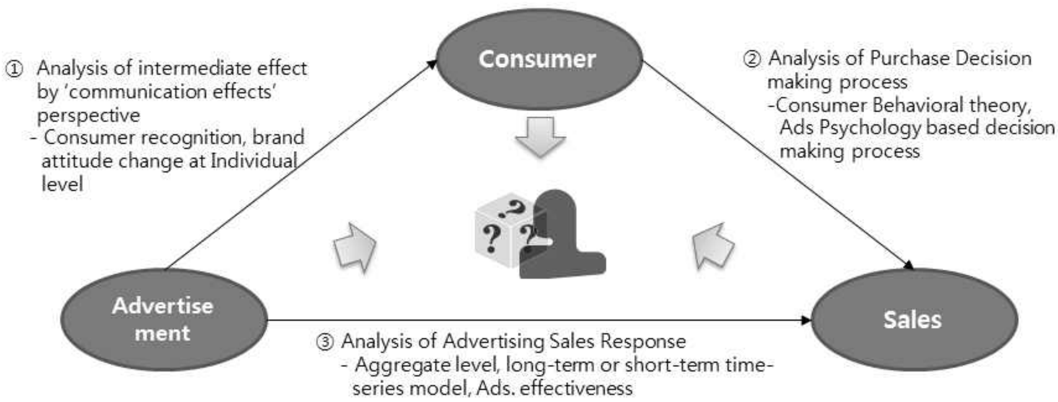

Figure 22. The limitation of previous literatures

Therefore, the current study proposes integrated models to measure advertising effects that include communications effects and sales effects, comprehensively. With respect to communication effects, the recent consumer behavior of Internet information searching is discussed in depth to determine the influence of this recent trend on the purchasing decision process. Internet search query data are analyzed to explain the various consumer behavior change phenomena concerning purchasing decision making. Random utility models depend on individual consumer survey data that are difficult to obtain. However, the current study uses Internet query data that does not depend on survey responses. Moreover, Internet data is real-time.

Chapter 3. Models

This study proposes advertising effects research that integrates communication and sales effects. In particular, this paper discusses consumers' behavioral changes due to Internet searches and the effects in the decision-making process when the communication effects are analyzed.

In this chapter, this study proposes an integrated model to analyze the TV advertising sales effects along with changes in consumer behavioral patterns, specifically the consumer decision-making process, caused by exposure to TV advertising. To measure the effect of advertising on sales, the model uses both communication effects as consumers' advertising response and the consumers' Internet search behavior to analyze the advertising effects, since the Internet search has become a new trend in the consumer decision-making process.

Several existing advertising measures are examined. Endogeneity and simultaneity in the advertising performance model are discussed. Then, the integrated models that resolve endogeneity and simultaneity are suggested.

This study also proposes an integrated model to analyze the TV advertising sales effects along with changes in consumer behavioral patterns, specifically the consumer decision-making process, caused by exposure to TV advertising. To measure the effect of advertising on sales, the model uses both communication effects as consumers' advertising response and the consumers' Internet search behavior to analyze the advertising effects, since the Internet search has become a new trend in the consumer decision-making process.

3.1 Measurement of the Advertisement Effects

In general, the advertising communication effects are measured based on the consumer behavior theory, which measures the response of advertising exposure, attitude, and advertising stimuli, as shown in Figure 23. According to the cognitive information processing (CIP) theory, consumers form an attitude toward the product based on their perception of the product, and then the attitude affects their purchase decisions (Sorce and Dewitz, 2007). McGuire (1968) suggested a “model of communication effects” based on the CIP theory.

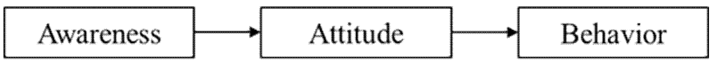

Figure 23. Consumer response after advertising exposure

Measuring TV advertisement effects traditionally involves three indicators: cognitive, emotional, and behavioral. The cognitive indicator shows product knowledge or persuasive message acceptance after exposure to advertising, measured by questionnaires based on recall and recognition. The measures are brand awareness, brand recall, top of mind, preference, and so forth.

The emotional indicator, which includes not only the evaluation of the specific brand but also the attitude toward advertising and emotional response, measures attitude change to the brand after watching the advertisement. The behavioral indicator measures how the advertising influences consumer behavior after consumers watch the advertisement through purchase intention change, purchase experiences, sales, and market share, which are widely used to measure TV advertising effectiveness (Han, Lee, & Park, 2009).

Additionally, the rating that is used in the commercial TV industry is applied to the performance measure. The measure represents the household acceptance rate of specific TV programing during a certain time period. This measure has been applied in the United States since the 1950s by Nilsen. The Nilsen introduced the people meter[2]' in 1986, and this method is currently applied worldwide.

Among these various communication effect measures, advertising awareness and preference were chosen in this study as the major indicators to measure advertising communication effectiveness because both indicators connect the flow of advertising sales effects and the consumer decision-making process of "awareness - comprehension - persuasion - behavior."

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[2] An audience measurement tool used to measure the viewing habits of TV and cable audiences.(source : Wikipedia)

“Advertising awareness” is a measure in the first stage from awareness to comprehension, and “preference” is for the second stage from comprehension to persuasion. Sales (or market share) are a final measure for the behavior stage.

3.2 Endogeneity and Causal-relationship in TV Advertising Effects with Sales

This study applies two econometric methods to verify the feasibility and effectiveness of the advertising measures.

Advertising effects, which are measured in terms of awareness, favorability, attitude toward advertising, and purchasing intent, do not play individually or independently. Instead, they are interactive and influence each other.

Previous studies show that the relationship between TV advertising and sales is influenced by various factors directly or indirectly related to consumers' responses to advertising. Each factor has interactive influences with causality and direction. Therefore, the fact that a variable could be not only an independent variable but also a dependent variable results in endogeneity and simultaneity.

To address this problem and verify the advertising measures quantitatively, this study suggests two econometric methods: the "simultaneous equation model and path analysis".

The simultaneous equation model addresses endogeneity. Endogeneity occurs because several advertising measure variables affect each other simultaneously.

Path analysis is conducted to prove the feasibility of each measure according to the casual effect model. Several variables exhibit causality and direction in a causal relationship model. Path analysis is a method to quantitatively analyze causal relationship models.

3.2.1 **Simultaneous Equation Model**

The proposed model in the study aims to identify endogeneity among variables, including the search query volume, to measure advertising sales effects along with awareness and preference as the current communicational measures of TV advertising effects that reflect the consumers' decision-making process.

The model links the indicators with consumer response in each stage of the advertising effects flow. The simultaneous equation is widely used to address these endogeneity issues (Amemiya, 1978; Greene, 2003; Heckman, 1978).

Once consumers recognize the advertised product after exposure to TV advertising, they gather more product information through various channels. One such channel is the Internet search. Consumers analyze and evaluate product information from their Internet search, and then they develop a preference and make a purchasing decision based on the preference, which leads to sales.

This flow makes it possible to incorporate the various advertising effects into the estimation model. In this flow, however, each step does not necessarily occur sequentially. The advertising exposure might affect only awareness and not preference.

Awareness could be an explanatory variable of advertising spend. At the same time, awareness itself could be a dependent variable affected by preference. Since an advertising budget is allocated in proportion to sales, it is highly likely that more sales products have a greater advertising budget. All of these effects are modeled as shown in Figure 24 and organized as follow ① ~ ⑤:

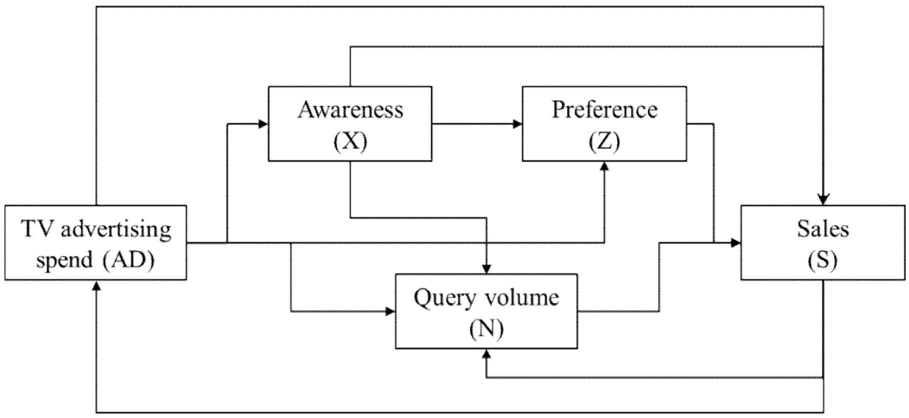


Figure 24. The endogeneity of advertising measures

① *Sales (S) = f1 [Advertising spend, Preference, Query volume, Awareness, Advertising spend (t−1) period]*

② *Advertising spend (AD) = f2 [Sales]*

③ *Preference (Z) = f3 [Advertising spend, Awareness, Advertising spend (t−1) period]*

④ *Awareness (X) = f4 [Advertising spend, Advertising spend (t−1) period, Sales, Sales (t−1) period]*

⑤ *Query volume (N) = ƒ5 [Advertising spend, Awareness, Advertising spend (t−1) period, Sales]*

This advertising sales effect model is consist of five equations with advertising effect variable in equations (3.1) ~ (3.5).

$$S_t = \alpha_1 AD_t + \alpha_2 Z_t + \alpha_3 N_t + \alpha_4 X_t + \alpha_5 AD_{t-1} + \varepsilon_1 \quad \text{(3.1)}$$

$$AD_t = \beta_1 S_t + \varepsilon_2 \quad \text{(3.2)}$$

$$Z_t = \gamma_1 X_t + \gamma_2 AD_t + \gamma_3 AD_{t-1} + \varepsilon_3 \quad \text{(3.3)}$$

$$X_t = \delta_1 AD_t + \delta_2 AD_{t-1} + \delta_3 S_t + \delta_4 S_{t-1} + \varepsilon_4 \quad \text{(3.4)}$$

$$N_t = \theta_1 AD_t + \theta_2 AD_{t-1} + \theta_3 X_t + \theta_4 S_t + \varepsilon_5 \quad \text{(3.5)}$$

where

S : Sales

AD : Advertising spend

Z : Preference

X : Awareness

N : Query volume

t : time period

The carry-over effects, which are generally analyzed in advertising effects, are considered in the proposed model by reviewing related previous literatures.

Clarke (1976) claimed that the duration of 90 percent of the total advertising effect is three to six months (Clarke, 1976). However, this applies only to frequently purchased, low-priced products. Han et al. (2009) argued that carry-over effects peak at one month after advertising exposure and disappear after four months (Han, Lee, & Park, 2009). According to the statistics from Korea CM Institute's annual report 2008, the carry-over effects of telecommunication service and handset advertising show that the awareness drastically decreases to 17 percent after one month and to 9 percent after two months. Also analyzed in this report are the carry-over effects of 658 advertisements. The result shows that 45.1 percent (297) of the total 658 advertisements have only a one-month effect and no longer any carry-over effects. Only 23.5 percent (155) of the total 658 advertisements have two-month effects.

Thus, telecommunication service and handset advertising have a shorter period of carry-over than the three to six months that Clarke (1976) suggested (Korea CM

Institute, 2011). Choi et al. (2009) noted that the characteristics of search query data are an immediate response, so query volume data are used to forecast trends in the near future rather than in the far future (Choi & Varian, 2009).

Considering consumer behavioral changes due to Internet searches, advertising carry-over effect is valid for only one month. After one more month, the search query volume is not a response of the advertising. Therefore, only the variables *(t-1)* period are used to deal with carry-over effects.

The estimation method of five simultaneous equations is the 3SLS (three-stage least squares) method. Several estimation methods exist to solve the endogenous problem in simultaneous equation systems. One such method is the estimation of limited information, a 2SLS (two-stage least squares) method. Another is the estimation method of full information, such as 3SLS, FIML (full information maximum likelihood) method. The 2SLS method is used for the estimation of simultaneous equations, and it estimates the system equations systematically using an instrument variable. Therefore, the correlation in disturbance terms of each equation cannot be considered. The estimation results are not asymptotically efficient; therefore, the 3SLS method is used. The 3SLS method assumes that the disturbance terms of each equation are correlated, and estimates all the system equations together.

The estimation process of 3SLS is as follows (Greene, 2003):

- 1st stage: make reduced form, and estimate the endogenous variable using ordinary least squares (OLS) method
- 2nd stage: with the estimate of 1st stage results place into original value, apply the OLS, and the calculated the variance-covariance matrix from the residual.
- 3rd stage: using the variance-covariance matrix from the 2nd stage, final estimate come out using generalized least square (GLS) method

The estimation process is as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} Z_1 & 0 & \cdots & 0 \\ 0 & Z_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & Z_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_M \end{bmatrix}$$

The system equations: $y = ZB + \varepsilon$

The correlation assumption of disturbance term: $E(\varepsilon\varepsilon') = \Sigma$, $E(\varepsilon) = 0$

The instrument variable: $\hat{z}_i = X\left(X'X\right)^{-1} X'z_i$ for each i , $\hat{Z}$ contain the instrumented values for all the regressors.

Using GLS,

$$\hat{B} = \left\{\hat{Z}'\left(\Sigma^{-1} \otimes I\right)\hat{Z}\right\}^{-1} \hat{Z}'\left(\Sigma^{-1} \otimes I\right) y \qquad \text{(a)}$$

If we take E to be the matrix of residuals from these estimates, a consistent estimate of Σ is,

$$\hat{\Sigma} = \frac{E'E}{n} \qquad \text{(b)}$$

Substitute the (b) into (a), the 3SLS estimates of the system parameters

$$\hat{B} = \left\{\hat{Z}'\left(\hat{\Sigma}^{-1} \otimes I\right)\hat{Z}\right\}^{-1} \hat{Z}'\left(\hat{\Sigma}^{-1} \otimes I\right) y$$

The asymptotic variance-covariance matrix of the estimator is

$$V_{\hat{B}} = \left\{\hat{Z}'\left(\hat{\Sigma}^{-1} \otimes I\right)\hat{Z}\right\}^{-1}$$

Applying above process to current study, the estimation results are calculated by 3SLS method (Greene, 2003) as follows:

- **1st stage:**

The structural form of the model is:

$$\mathbf{y}_t'\mathbf{\Gamma} + \mathbf{x}_t'\mathbf{B} = \boldsymbol{\varepsilon}_t'$$

where

$$\mathbf{y}_t' = \begin{bmatrix} S_t & AD_t & Z_t & X_t & N_t \end{bmatrix}$$

$$\mathbf{x}_t' = \begin{bmatrix} S_{t-1} & AD_{t-1} \end{bmatrix}$$

$$\boldsymbol{\varepsilon}_t' = \begin{bmatrix} \varepsilon_{1t} & \varepsilon_{2t} & \varepsilon_{3t} & \varepsilon_{4t} & \varepsilon_{5t} \end{bmatrix}$$

and

$$\mathbf{\Gamma} = \begin{bmatrix} 1 & -\beta_1 & 0 & -\delta_3 & -\theta_4 \\ -\alpha_1 & 1 & -\gamma_2 & -\delta_1 & -\theta_1 \\ -\alpha_2 & 0 & 1 & 0 & 0 \\ -\alpha_4 & 0 & -\gamma_1 & 1 & -\theta_3 \\ -\alpha_3 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} 0 & 0 & 0 & -\delta_4 & 0 \\ -\alpha_5 & 0 & -\gamma_3 & -\delta_2 & -\theta_2 \end{bmatrix}$$

Let $\mathbf{Y} = \begin{bmatrix} \mathbf{y}_1' \\ \vdots \\ \mathbf{y}_T' \end{bmatrix}$, $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1' \\ \vdots \\ \mathbf{x}_T' \end{bmatrix}$, $\mathbf{E} = \begin{bmatrix} \boldsymbol{\varepsilon}_1' \\ \vdots \\ \boldsymbol{\varepsilon}_\mathbf{T}' \end{bmatrix}$

The structural form of the model in terms of the full set of T observations:

$$\mathbf{Y\Gamma} + \mathbf{XB} = \mathbf{E}$$

Reduced form of the model:

$$\mathbf{Y} = \mathbf{X\Pi} + \mathbf{V}$$

where $\mathbf{\Pi} = \mathbf{B\Gamma}^{-1}$ and $\mathbf{V} = \mathbf{E\Gamma}^{-1}$

For all T observations, the nonzero terms in the j th equation ($j = 1,\ldots,M$) are

$$\begin{aligned}\mathbf{y}_j &= \mathbf{Y}_j\boldsymbol{\gamma}_\mathbf{j} + \mathbf{X}_j\boldsymbol{\beta}_\mathbf{j} + \boldsymbol{\varepsilon}_\mathbf{j} \\ &= \mathbf{Z}_\mathbf{j}\boldsymbol{\delta}_\mathbf{j} + \boldsymbol{\varepsilon}_\mathbf{j}\end{aligned}$$

where $\mathbf{Y}_\mathbf{j}$ stands for included endogenous variable and $\mathbf{X}_j$ stands for included exogenous variable.

Then $\mathbf{Z}_j = \left[\mathbf{Y}_\mathbf{j}, \mathbf{X}_j\right]$.

For $\mathbf{Y}_\mathbf{j}$, reduced-form equations are $\mathbf{Y}_j = \mathbf{X\Pi}_\mathbf{j} + \mathbf{V}_\mathbf{j}$

By OLS method,

$\hat{\mathbf{Y}}_j = \mathbf{X}\left[\left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{Y}_j\right]$: using these for the instruments for $\mathbf{Y}_\mathbf{j}$

- **2nd stage:**

Estimate $\delta_{j,2SLS}$ by least squares regression of $\mathbf{y}_j$ on $\hat{\mathbf{Y}}_j$ and $\mathbf{X_j}$

$$\hat{\delta}_{j,2SLS} = \begin{bmatrix} \hat{\mathbf{Y}}_j'\hat{\mathbf{Y}}_j & \hat{\mathbf{Y}}_j'\mathbf{X}_j \\ \mathbf{X}_j'\hat{\mathbf{Y}}_j & \mathbf{X}_j'\mathbf{X}_j \end{bmatrix}^{-1} \begin{bmatrix} \hat{\mathbf{Y}}_j'\mathbf{y}_j \\ \mathbf{X}_j'\mathbf{y}_j \end{bmatrix}$$
$$= \left[\hat{\mathbf{Z}}_j'\hat{\mathbf{Z}}_j\right]^{-1} \hat{\mathbf{Z}}_j'\mathbf{y}_j$$

where $\hat{\mathbf{Z}}_j = \mathbf{X}\left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{Z}_j$

Computing variance-covariance ($\hat{\mathbf{\Sigma}}$) using

$$\hat{\sigma}_{ij} = \frac{\left(\mathbf{y}_i - \mathbf{Z}_i\hat{\delta}_{i,2SLS}\right)'\left(\mathbf{y}_j - \mathbf{Z}_j\hat{\delta}_{\mathrm{j},2SLS}\right)}{T}$$

- **3rd stage:**

Using GLS method

$$\hat{\delta}_{3SLS} = \left[\hat{\mathbf{Z}}'\left(\mathbf{\Sigma}^{-1} \otimes \mathbf{I}\right)\hat{\mathbf{Z}}\right]^{-1} \hat{\mathbf{Z}}'\left(\mathbf{\Sigma}^{-1} \otimes \mathbf{I}\right)\mathbf{y} \quad \text{where} \quad \hat{\mathbf{Z}} = diag\left[\hat{\mathbf{Z}}_1 \quad \cdots \quad \hat{\mathbf{Z}}_M\right]$$

3.2.2 **Structural Equation Model: Path Analysis**

The simultaneous equation model is used to verify advertising measures including Internet search data and to address the endogeneity problem within each measure, such as awareness and preference.

Other aspects must be verified in addition to endogeneity in the current study. The measures selected in this study have limitations, one of which is causality and direction. Each factor has an interactive influence on causality and direction. Moreover, each factor that is used in the proposed model is included in advertising effect theories such as advertising sales effect, communication effect, and the consumer behavior model. Therefore, the integrated model that includes each factor must be verified. The path analysis in the structural equation model is appropriate for examining the validity and feasibility of the proposed integrated advertising effect model in this study.

Figure 25 shows that the structural equation model estimates the combined latent variable and the measured variable.

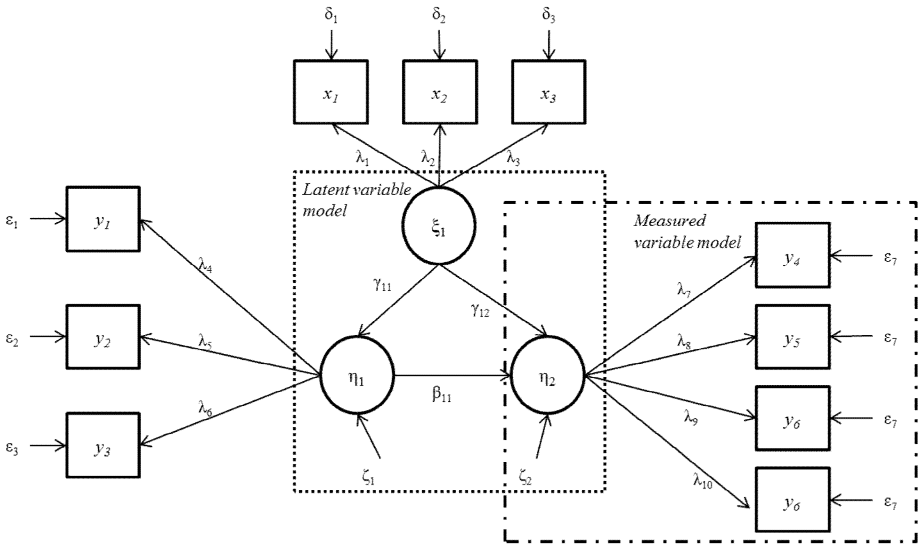


Figure 25. Structural equation model (Source : Loehlin, 1992)

The general structural equation model, developed by Karl Joreshog (1970), combines the conventional statistical analysis methods: confirmatory factor analysis, based on sociology and psychology, and multiple regression and path analysis, based on econometrics (Goldberger & Duncan, 1973).

The structural equation model has two advantages not evident with multivariate statistical analysis. The structural equation model facilitates the estimation of a series of dependence relationships simultaneously and reflects measurement error in the estimation process (Lee & Lim, 2011).

The advantage of structural equation model can be summarized by the following three points. First, measurement error can be controlled because several measure variables originating from common variates are used. Second, parameter estimation is easier to use than regression models. Parameter estimation should be both dependent and independent. However, in the regression model, parameter values should perform a single. Third, the statistical evaluation of the theoretical model is possible using a structural equation model. It is possible to determine the fit of the real data with the theoretical model and accept or modify the model (Kim, Kim, & Hong, 2009).

The structural equation model is also effective in the current model for the examination of the consumer purchasing decision. Joseph (2010) shows that the use of the structural equation model is effective in explaining the causality of the purchasing decision-making process (Priester, 2010).

Survey data can be gathered to conduct a confirmatory analysis of latent variables to be applied to a general structural equation model. However, no latent variables exist in this study. The data are measured variables such as search query volume, awareness, preference, sales, and advertising expenditure. Therefore, a confirmatory analysis of latent variables and associated verification of the variables was not conducted in the current study.

Path analysis is developed by Sewell Wright in 1960s. It is used to verify the relationship between respective variables (Loehlin, 1992; Wright, 1960). The purpose of path analysis is to examine hypotheses based on theoretical considerations and model feasibility. According to Wright (1960), there are strict assumptions associated with path analysis.

> " (a) No loops are allowed. In tracing from one variable to another, you cannot pass through the same variable twice following a particular route…
>
> (b) No going forward and then backward. Once you have traveled along a route forward, you cannot travel backward to get to the variable at the end point…
>
> (c) Only one curved arrow is allowed in tracing from the first variable to the last variable in any route…" (Loehlin, 1992)

Figure 26 illustrates path analysis and the examination of the causality and direction of variables by the covariate or correlation coefficient. This process reveals the direct and indirect effect of variables.

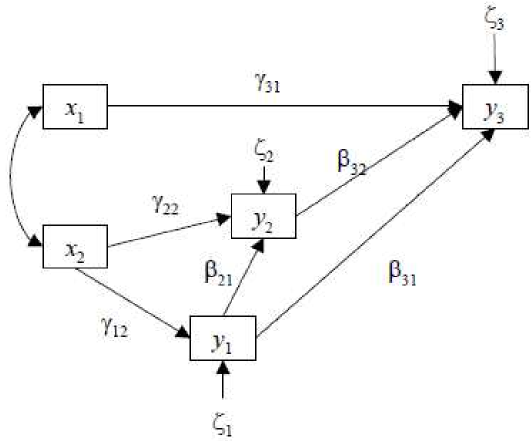


Figure 26. Path analysis model

(Source : Loehlin, 1992)

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ \beta_{21} & 0 & 0 \\ \beta_{31} & \beta_{32} & 0 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} + \begin{bmatrix} 0 & \gamma_{12} \\ 0 & \gamma_{22} \\ \gamma_{31} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix}$$

$$y = By + \Gamma x + \zeta \qquad (3.6)$$

$$Cov(y) = \Phi = \begin{bmatrix} \phi_{11} & \phi_{21} \\ \phi_{12} & \phi_{22} \end{bmatrix}, \quad Var(x) = \Psi = \begin{bmatrix} \psi_{11} & 0 & 0 \\ 0 & \psi_{22} & 0 \\ 0 & 0 & \psi_{33} \end{bmatrix}$$

$$\sum\theta = \begin{bmatrix} \sum_{yy}\theta & \sum_{yx}\theta \\ \sum_{xy}\theta & \sum_{xx}\theta \end{bmatrix}$$

$$= \begin{bmatrix} \gamma_{11}^2\phi_{11} + \varphi_{11} & & \\ \beta_{21}(\gamma_{11}^2\phi_{11} + \varphi_{11}) & \beta_{21}(\gamma_{11}^2\phi_{11} + \varphi_{11}) + \varphi_{22} & \\ \gamma_{11}\phi_{11} & \beta_{21}\gamma_{11}\phi_{11} & \phi_{11} \end{bmatrix}$$

The null hypothesis is :

$$H_0 : \Sigma - \Sigma(\theta) = 0$$

Where,

Σ : the population covariance matrix of observed variables (unobservable).

Σ(θ) : the model-based covariance matrix written as a function of θ.

However, Σ is unobservable because the coefficient of the path represents parameters that must be estimated. Therefore, I introduce the sample covariance matrix of the observed variable S. We choose $\hat{\theta}$ so that $\sum\hat{\theta}$ is close to S. Finally, the fitting function F is introduced to determine that the optimal value of fitted residual matrix is 0.

$$min\ F\ (S,\ \hat{\Sigma})$$

where, F is fitted function.

Figure 25 illustrates that the direct effect implies that on independent variable influences another dependent variable directly and the parameter gamma (γ) and beta *(β)*. Indirect effect implies that one independent variable influences several dependent variables by the parameters. Total effect is the sum of direct effect and indirect effect.

Path analysis could be considered to be several multiple regression analyses. However, path analysis differs because there is causality order within variables. There is no causality order in regression analysis. There are cause and effect relationships within variables in path analysis; however, this is not the case with causality order. The independent variables only used forecasting dependent variables in the regression. Therefore, the directional order of variables can be examined using path analysis. Several assumptions are required for the application of path analysis.

First, the premise that causal order within a variable is known is assumed. Second, the assumptions used in regression, such as linearity and additivity, are required.

The hypotheses of advertising effect model to path analysis are as followed *(H1) ~ (H4)*.

H1 : Advertising spend has positive influence on sales effect.

H2 : Advertising spend positive influences on consumers' knowledge, and this represented by the recognition measure.

H3 : the level of consumer recognition influences on consumer persuasion, and this represented by the preference change

H4 : advertising spend and recognition level influence search query volume.

Each ultimate factor in the diagram must be connected with each other to indicate a possible correlation. It is assumed here that all relations are linear. Using the path analysis model, it is possible to analyze the causality and direction among various advertising effects. Analyzing causality among variables clarifies how advertising influences each stage of the consumers' decision-making process.

Figure 27 illustrates the advertising measure path diagram of the proposed model as mentioned in the above theory and hypotheses.

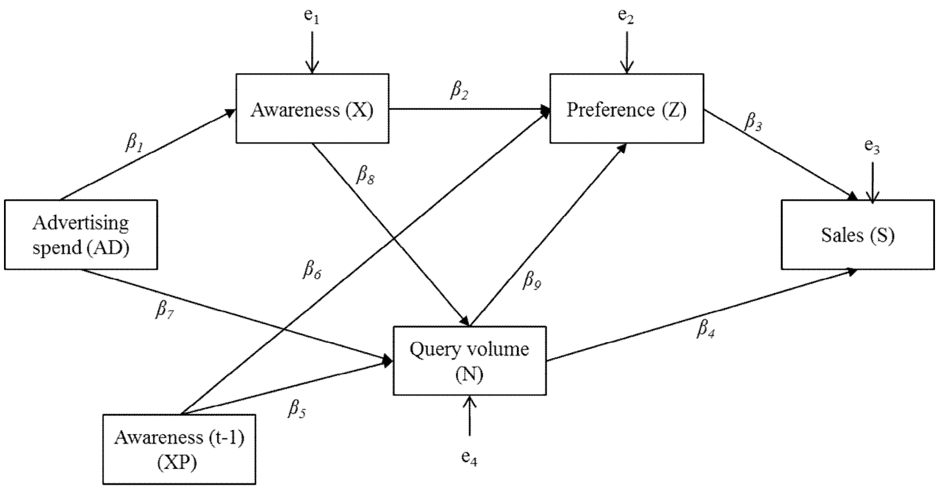


Figure 27. Path diagram of advertising measures for the path analysis

$$X = \beta_1 AD + e_1 \quad (3.7)$$

$$Z = \beta_2 X + \beta_6 XP + \beta_9 N + e_2 \quad (3.8)$$

$$S = \beta_3 Z + \beta_4 N + e_3 \quad (3.9)$$

$$N = \beta_7 AD + \beta_5 XP + \beta_8 X + e_4 \quad (3.10)$$

To estimate the parameters, the variance-covariance matrix should be calculated. The variances and covariances of current model are as follows:

- **Variance**

$$\sigma_X^2 = \beta_1^2\sigma_{AD}^2 + \sigma_{e_1}^2$$

$$\begin{aligned}
\sigma_Z^2 &= \beta_2^2\sigma_X^2 + \beta_6^2\sigma_{XP}^2 + \beta_9^2\sigma_N^2 + \sigma_{e_2}^2 \\
&= \beta_2^2\left(\beta_1^2\sigma_{AD}^2 + \sigma_{e_1}^2\right) + \beta_6^2\sigma_{XP}^2 + \beta_9^2\left(\beta_7^2\sigma_{AD}^2 + \beta_5^2\sigma_{XP}^2 + \beta_8^2\left(\beta_1^2\sigma_{AD}^2 + \sigma_{e_1}^2\right) + \sigma_{e_4}^2\right) + \sigma_{e_2}^2 \\
&= \left(\beta_1^2\beta_2^2 + \beta_7^2\beta_9^2 + \beta_1^2\beta_8^2\beta_9^2\right)\sigma_{AD}^2 + \left(\beta_6^2 + \beta_5^2\beta_9^2\right)\sigma_{XP}^2 + \left(\beta_2^2 + \beta_8^2\beta_9^2\right)\sigma_{e_1}^2 + \sigma_{e_2}^2 + \beta_9^2\sigma_{e_4}^2
\end{aligned}$$

$$\begin{aligned}
\sigma_S^2 &= \beta_3^2\sigma_Z^2 + \beta_4^2\sigma_N^2 + \sigma_{e_3}^2 \\
&= \beta_3^2\begin{Bmatrix}\left(\beta_1^2\beta_2^2 + \beta_7^2\beta_9^2 + \beta_1^2\beta_8^2\beta_9^2\right)\sigma_{AD}^2 + \left(\beta_6^2 + \beta_5^2\beta_9^2\right)\sigma_{XP}^2 \\ +\left(\beta_2^2 + \beta_8^2\beta_9^2\right)\sigma_{e_1}^2 + \sigma_{e_2}^2 + \beta_9^2\sigma_{e_4}^2\end{Bmatrix} \\
&\quad + \beta_4^2\left\{\left(\beta_7^2 + \beta_1^2\beta_8^2\right)\sigma_{AD}^2 + \beta_5^2\sigma_{XP}^2 + \beta_8^2\sigma_{e_1}^2 + \sigma_{e_4}^2\right\} + \sigma_{e_3}^2 \\
&= \left(\beta_4^2\beta_7^2 + \beta_1^2\beta_2^2\beta_3^2 + \beta_1^2\beta_4^2\beta_8^2 + \beta_3^2\beta_7^2\beta_9^2 + \beta_1^2\beta_3^2\beta_8^2\beta_9^2\right)\sigma_{AD}^2 + \left(\beta_3^2\beta_6^2 + \beta_4^2\beta_5^2 + \beta_3^2\beta_5^2\beta_9^2\right)\sigma_{XP}^2 \\
&\quad + \left(\beta_2^2\beta_3^2 + \beta_4^2\beta_8^2 + \beta_3^2\beta_8^2\beta_9^2\right)\sigma_{e_1}^2 + \beta_3^2\sigma_{e_2}^2 + \sigma_{e_3}^2 + \left(\beta_4^2 + \beta_3^2\beta_9^2\right)\sigma_{e_4}^2
\end{aligned}$$

$$\sigma_N^2 = \left(\beta_7^2 + \beta_1^2\beta_8^2\right)\sigma_{AD}^2 + \beta_5^2\sigma_{XP}^2 + \beta_8^2\sigma_{e_1}^2 + \sigma_{e_4}^2$$

- **Covariance**

$$\sigma\left(X,\mathrm{Z}\right) = \left(\beta_1^2\beta_2 + \beta_1\beta_7\beta_9 + \beta_1^2\beta_8\beta_9\right)\sigma_{AD}^2 + \left(\beta_1\beta_6 + \beta_1\beta_5\beta_9\right)\sigma_{AD,XP} + \left(\beta_2 + \beta_8\beta_9\right)\sigma_{e_1}^2$$

$$\sigma(X,N)=\left(\beta_1\beta_7+\beta_1^2\beta_8\right)\sigma_{AD}^2+\beta_1\beta_5\sigma_{AD,XP}+\beta_8\sigma_{e_1}^2$$

$$\begin{aligned}\sigma(X,S)=&\left(\beta_1\beta_2^2\beta_3+\beta_1\beta_4\beta_7+\beta_1^2\beta_4\beta_8+\beta_1\beta_3\beta_7\beta_9+\beta_1^2\beta_3\beta_8\beta_9\right)\sigma_{AD}^2\\&+\left(\beta_1\beta_3\beta_6+\beta_1\beta_4\beta_5+\beta_1\beta_3\beta_5\beta_9\right)\sigma_{AD,XP}+\left(\beta_2\beta_3+\beta_4\beta_8\right)\sigma_{e_1}^2\end{aligned}$$

$$\begin{aligned}\sigma(Z,S)=&\left(\beta_3\beta_6^2+\beta_4\beta_5\beta_6+\beta_3\beta_5^2\beta_9^2+2\beta_3\beta_5\beta_6\beta_9\right)\sigma_{XP}^2\\&+\begin{pmatrix}\beta_4\beta_7^2\beta_9+\beta_3\beta_7^2\beta_9^2+\beta_1\beta_3\beta_5\beta_9^2+\beta_1^2\beta_4\beta_8^2\beta_9+\beta_1\beta_2\beta_3\beta_7\beta_9\\+\beta_1\beta_3\beta_7\beta_8\beta_9^2+\beta_1^2\beta_2\beta_3\beta_5\beta_9+\beta_1^2\beta_3\beta_5\beta_8\beta_9^2\end{pmatrix}\sigma_{AD}^2\\&+\begin{pmatrix}\beta_4\beta_6\beta_7+\beta_1\beta_2\beta_3\beta_6+\beta_1\beta_3\beta_6\beta_9+\beta_1\beta_4\beta_6\beta_8+\beta_1\beta_3\beta_5^2\beta_9^2\\+2\beta_3\beta_5\beta_7\beta_9+2\beta_3\beta_6\beta_7\beta_9+\beta_1\beta_2\beta_3\beta_5\beta_9+\beta_1\beta_3\beta_5\beta_6\beta_9+\beta_1\beta_3\beta_5\beta_8\beta_9^2\end{pmatrix}\sigma_{AD,XP}\\&+\left(\beta_4\beta_5^2\beta_9+\beta_2\beta_3\beta_5\beta_9+\beta_3\beta_5\beta_8\beta_9^2\right)\sigma_{e_1}^2+\beta_4\sigma_{e_2}^2+\left(\beta_3\beta_9^2+\beta_4\beta_9\right)\sigma_{e_4}^2\end{aligned}$$

$$\begin{aligned}\sigma(Z,N)=&\left(\beta_5\beta_6+\beta_5^2\beta_9\right)\sigma_{XP}^2\\&+\left(\beta_7^2\beta_9+\beta_1\beta_2\beta_7+\beta_1^2\beta_2\beta_5+\beta_1\beta_5\beta_7\beta_9+\beta_1\beta_7\beta_8\beta_9+\beta_1^2\beta_5\beta_8\beta_9\right)\sigma_{AD}^2\\&+\left(\beta_6\beta_7+\beta_1\beta_2\beta_5+\beta_1\beta_5\beta_6+\beta_1\beta_5^2\beta_9+2\beta_5\beta_7\beta_9+\beta_1\beta_5\beta_8\beta_9\right)\sigma_{AD,XP}\\&+\left(\beta_2\beta_5+\beta_4\beta_5\beta_8\right)\sigma_{e_1}^2+\beta_9\sigma_{e_4}^2\end{aligned}$$

$$\begin{aligned}\sigma(S,N)=&\left(\beta_4\beta_5^2+\beta_3\beta_5\beta_6+\beta_3\beta_5^2\beta_9\right)\sigma_{XP}^2\\&+\begin{pmatrix}\beta_4\beta_5^2+\beta_4\beta_7^2+\beta_1^2\beta_4\beta_8^2+\beta_3\beta_5\beta_6+\beta_3\beta_5^2\beta_9+\beta_3\beta_7^2\beta_9+\beta_1\beta_2\beta_3\beta_7\\+\beta_1^2\beta_2\beta_3\beta_8+\beta_1^2\beta_3\beta_8^2\beta_9+2\beta_1\beta_4\beta_7\beta_8+2\beta_1\beta_3\beta_7\beta_8\beta_9\end{pmatrix}\sigma_{AD}^2\\&+\begin{pmatrix}\beta_3\beta_6\beta_7+\beta_1\beta_2\beta_3\beta_5+\beta_1\beta_3\beta_6\beta_8+2\beta_1\beta_4\beta_5\beta_8+\\2\beta_2\beta_4\beta_5\beta_7+2\beta_3\beta_5\beta_7\beta_9+2\beta_1\beta_3\beta_5\beta_8\beta_9\end{pmatrix}\sigma_{AD,XP}\\&+\left(\beta_4\beta_8^2+\beta_2\beta_3\beta_8+\beta_2\beta_8^2\beta_9\right)\sigma_{e_1}^2+\beta_4\sigma_{e_4}^2\end{aligned}$$

There are two types of estimation method for path analysis, the least square method and the maximum likelihood method. The least square method uses iteration to prove the fitness of parameter estimates. The estimation is conducted to minimize the fitted residual matrix, which is composed of the population covariance matrix minus the model implied matrix. The maximum likelihood method uses the probability density function as the fitting function to estimate parameter values.

The maximum likelihood estimation (MLE) method and the generalized least square (GLS) method are used in structural equation models. The MLE is consistent and is an asymptotically efficient estimator for a large sample.

The MLE and GLS estimators are scale invariant. Therefore, the parameter estimate is identical for a variance-covariance matrix or a correlation matrix. If the data are from large sample with a normal distribution, MLE is appropriate for the chi-square test. However, if the data have multivariate normal distribution, GLS is appropriate. Finally, if the data are not normally distributed, weighted least square (WLS) is desirable.

3.3 Behavioral Model for Aggregate Demand and Consumer Preference

This section models the relationship of consumer preference and search query data using two different methods.

Consumer preference for a product or service is represented in direct or indirect ways. Search query data was collected from consumer Internet searches concerning a product or service. The data can be considered as aggregate level consumer interest with respect to a new product or service.

Consumer Internet searching behavior is the focus of analysis in the current study. Search query data implies consumer preference for a new product or new service. Therefore, the suggested model focuses on examining consumer behavior patterns based on the utility model using search query data.

General variables, such as product attributes that affect consumer utility are used in a random utility model. Additionally, search query data is used as a variable that influences consumer choice.

The sale of new products or new services represents consumer choice based on preference. Advertising expenditure could represent a trigger that influences sales of new products or new services. Therefore, advertising performance could be measured by utility structure.

The choice probability model considered in this section, is based on the random utility model and are derived under the assumption that decision- makers choose alternatives to maximize their utility.

When a consumer *n* chooses the *i* alternative from among three alternatives, the utility of consumer n is described as the following Equation (3.11)

$$U_{in} = V(X_{in} \; ; \beta) + \gamma F_{in} + \varepsilon_{in} \qquad (3.11)$$

where

i : telecom company in Korea (KT, LGT, SKT)

n : decision maker

X_{in} *: attributes of alternative i (including the characteristics of TV ads.), awareness and preference of advertising*

β *: parameter that capture the attributes*

F_{in} *: query count share of those people in the group of decision maker n who chose alternative i*

γ *: parameter that capture the influence of internet search*

This equation assumes that the utility of alternative ***i*** consists of the indirect utility (V) caused by attributes of alternative ***i*** (X_{in}), the influence of an Internet search (F_{in}), and the stochastic contribution (ε_{in}) of the utility. The stochastic contribution cannot be observed by the researchers. The influence of an Internet search represents the query count share of the individuals in the group of decision maker n who chose alternative ***i***.

Equation (3.11) has endogeneity limitations because the second term (F_{in}) is correlated with indirect utility (V) and stochastic term (ε_{in}). Therefore, the BLP method suggested by Berry et al. (1995) is used (Berry, Levinsohn, & Pakes, 1995; Walker, Ehlers, Banerjee, & Dugundji, 2011).

To get rid of endogeneity problem, stochastic term (ε_{in}) are divided two part based on that whether correlation exists or not as shown in Equation (3.12).

$$U_{in} = V\,(X_{in}\;;\,\beta) + \gamma F_{in} + \ddot{\varepsilon}_{in} + \dot{\varepsilon}_{in} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (3.12)$$

This equation can be rearranged as follows, see equation (3.13) (3.14) and (3.15).

$$U_{in} = [\gamma F_{in} + \ddot{\varepsilon}_{in}] + V\,(X_{in}\,;\,\beta) + \dot{\varepsilon}_{in} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (3.13)$$

$$U_{in} = \alpha_{in} + V(X_{in}; \beta) + \dot{\varepsilon}_{in} \quad \cdots\cdots (3.14)$$

where

$$\alpha_{in} = [\gamma F_{in} + \ddot{\varepsilon}_{in}] \quad \cdots\cdots (3.15)$$

In equation (3.13), γF_{in} and $\dot{\varepsilon}_{in}$ are joined because two terms are correlated. The squared bracket term is replaced with a constant term (α_{in}) in equation (3.14). There is no correlation term in equation (3.14); therefore, the endogeneity issue is solved and it is possible to estimate parameter (β). To estimate parameter (β) of the indirect utility V, the explanatory variables X_{in} are product attributes such as mobile device specifications, price, awareness, and preferences concerning TV advertising.

To estimate equation (3.14), it is possible to obtain the parameter α, β. However, the parameter γ, which represent the influence of the Internet search, could not be estimated directly. To obtain parameter γ, equation (3.15) must be estimated separately. Endogeneity exists because the parameters γ and ε are correlated. Therefore, the two-stage least square (2SLS) method is applied. Instrument variable (I) is required when using the two-stage least square method. The instrument variables are set as follows:

I_i: average advertising spend, lag variable of advertising spend

Equation (3.15) using instrument variable (I_i) can be rearranged as follows:

$$F_{in} = \theta_i + \theta_F I_{in} + \upsilon_{in} \quad \cdots\cdots (3.16)$$

$$\hat{F}_{in} = \hat{\theta}_i + \hat{\theta}_F I_{in} \quad \cdots\cdots (3.17)$$

$$\alpha_{in} = \gamma_i + \gamma_F \hat{F}_{in} + \ddot{\varepsilon}_{in} \quad \cdots\cdots (3.18)$$

By estimating the parameter value of equation (3.16), it is possible to obtain the result of θ. If θ is known as the equation (3.17), equation (3.18) can be estimated because there is no endogeneity. Finally, the parameter value of equation (3.18) could be estimated.

The data used in the current study do not reflect individual consumer demographic information. The data are the result of consumer choice and represent aggregate level demand. Therefore, the BLP method is applied in the estimation (Berry et al., 1995; Train, 2009). Generally, price is endogenous variable in the choice model. Therefore, instrument variables are introduced. However, price used as an attribute in this model is not endogenous for two reasons. First, price is not a normal market value. Price is a central factor in consumer choice, because the retail price of each product is real. Contrastingly, the price of a mobile phone is face value. The majority of consumers pay monthly bill instead of one lump sum payment. Moreover, a subsidy is provided to render the actual price less than face value. Second, consumers who search for new mobile phone information after consuming TV advertising might decide on a product regardless of price. A consumer might search the Internet to determine the product specifications. Additionally, the focus of the current study is social influence in consumer choice.

This model facilitates the analysis of the advertising sales effect based on the consumer utility structure. The influence of the consumer Internet search is included in the model; therefore, search query data could be a measure for the analysis of the advertising sales effect. Previous literature concerning consumer choice and utility models have addressed price and product attributes. Moreover, the general utility model data is obtained from a consumer survey that captures stated preferences. However, the current study suggests that the social influence on consumer choice could be measured by search query volume (the variable F).

3.4 Characteristic Comparison of Models

This study aims to analyze the internet search influence on consumer purchasing decision and applies three models for these purposes as discussed above. In this section, the summaries of three models and are presented in Table 4:

Table 4. Comparison of models

	1. Simultaneous Equation model	**2. SEM-Path analysis**	**3. Random Utility model and BLP correction**
Purpose	To verifying the level of contribution of each advertising measure according to the decision- making process to sales response. To address endogeneity in advertising measures.	To structure consumer behavior based on the decision-making process. To verify the causality and direction of advertising measures.	To analyze consumer preference based on utility structure. To use Internet search data as aggregate demand, verifying the contribution of each advertising measure with product attributes.

Key features	The structure of consumer purchasing decision-making '(recognition → knowledge → confirmation → action)' and the advertising response. Examination of the relationship of existing TV advertising measures with new measures. • The feasibility of existing advertising measures. • The relationship of existing advertising measures and the proportion of explanatory variables. • The feasibility of the new measure (Internet search query volume) as a measure of consumer behavior change.	The integration of existing advertising effect models. The use of internet search data, represented by aggregate demand excluding individual consumer attributes.

Chapter 4. Empirical Analysis

4.1 Data Description

The data for this study are based on the monthly terrestrial TV advertising expenses of three major mobile carriers in Korea from January 2008 to December 2011, and current advertising performance indicators such as awareness and preference. Moreover, the search query volumes and the number of new subscribers associated with the TV advertising were analyzed.

In Korea, terrestrial TV advertising has the greatest share of total advertising spend, as shown in Table 5. TV is the most powerful of the advertising media, and strongly influences consumers' preferences and their awareness of new products and services.

Table 5. Advertising spending in Korea

(unit : 100 million won)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Subtotal	44,014	52,839	50,328	46,695	45,267	46,242	46,525	43,151	38,335	43,119

- TV	19,537	24,394	23,671	22,500	21,492	21,839	21,076	18,997	16,709	19,307
- Radio	2,372	2,780	2,751	2,653	2,683	2,799	2,807	2,769	2,231	2,565
- Newspaper	17,500	20,200	18,900	17,460	16,724	17,013	17,801	16,581	15,007	16,438
- Magazine	4,605	5,465	5,006	4,256	4,368	4,591	4,841	4,804	4,388	4,889
New media[3]	2,933	4,195	5,675	7,957	10,599	14,650	18,706	20,762	20,609	25,748
Etc.	10,192	11,407	13,865	13,749	14,673	15,448	14,666	14,023	13,616	15,555
Total	57,138	68,441	69,868	68,401	70,539	76,340	79,897	77,971	72,560	84,501

Source: KOBACO, Cheil Worldwide ‘Advertising Yearbook 2011, http://www.index.go.kr/egams/stts/jsp/potal/stts/PO_STTS_IdxMain.jsp?idx_cd=1649

The reason I chose data from three mobile service providers is that the mobile devices were the most popular web search items when consumers obtained product information from the web and made a purchasing decision, so that the advertising effects could be effectively measured.

Among the various ICT devices, mobile phones and wireless services have a strongly influenced by early adopters. The Internet enables the early adopters to create online communities to share not only price information but also professional reviews of

[3] CATV, Satellite TV(since 2004), Online, Mobile, IPTV, DMB

device specifications. Hence, consumers spontaneously explore the Internet for information about new models and services even before the new device is launched.

Furthermore, current study focused on the telecom industry. Because telecom advertising performed remarkably in terms of advertising spend, advertising effectiveness, and consumer awareness.

Through domestic terrestrial broadcasting in Korea in 2008, the total number of TV advertisements was 2,231, and the total advertising spending was $1.5 billion. By industry, “computer and telecommunications” spent the most on advertising at $248.2 million, accounting for 16.4 percent of the total advertising spending. Being the first year the new 3G mobile services were launched, three mobile service providers deployed massive advertising campaigns to dominate the market and to lead this new service. Although the Korean economy was in recession triggered by the financial crisis in the U.S. in 2008, all telecom industry advertising effectively raised their brand awareness and were ranked as the top 10 preferred brands out of 989 brands as shown in Table 6.

Table 6. The liking for TV advertising of top 10 brands in 2008

(annually accumulated)

Rank	Brand name	Industrial sector	Ad spend[1)] (million won)	Minding Rating Point[2)] (% p)
1	SHOW	Computer and telecommunications	21,551	154.12
2	SK telecom T	Computer and telecommunications	35,167	146.95
3	Himart	Retail	24,460	86.23
4	Digital exciting anycall	Computer and telecommunications	32,312	59.65
5	Myoungin igatan	Pharmaceutical and medical	12,424	56.19
6	S oil PR	Basic industry	8,528	52.02
7	LG cyon	Computer and telecommunications	17,868	48.95
8	LG telecom OZ	Computer and telecommunications	16,541	47.92
9	BC card PR	Financial, Insurance and stock	7,630	38.10
10	Maxim	Food	4,698	37.25

1) Ad spend : terrestrial TV program and piece advertisement in Seoul metropolitan area
2) Mind Rating Point (% p) : monthly unaided recall (annually accumulated)

Source: Korea CM Institute

The monthly advertising spending and advertising performance indicators, including favorability and preference, are based on statistics from the Korea CM Institute, which measures awareness, favorability, and preference of TV advertising from 1,200 consumer panels on a monthly basis and issues annual reports on advertising effects and effectiveness.

The consumer panel comprised males and females, aged 10 to 59 years, living in Seoul and surrounding cities, and 20 percent of the members were replaced every month. Research methodology consisted of panel members answering the questionnaire by revealing their favorite advertising and the brand or company names. Specifically, they recalled what resonated with the advertising after their exposure to it, and so the methodology considered various aspects of the communications.

The keyword search results from Google trends (http://google.com/trends) and Naver trend (http://trend.naver.com) were analyzed for the search query volume, which reflected the new consumer behavioral pattern. The monthly trends data for three mobile service providers' TV advertisements on their mobile devices and 3G services are analyzed in the study. Finally, the sales data (number of new subscribers) of the new 3G mobile phone are obtained from the statistics of the Korea Communications Commission. The data used in this study are summarized in Table 7.

Table 7. Descriptive statistics of variables (N = 144)

Variable	Definition	Mean	Variance
Sales (number of subscribers)	Number of new subscribers each month	70,713	3.587E9
Advertising spend (million dollars)	Total amount of advertising spend per month in each company	2.36	318.28
Awareness (percent)	Average percentage of the people aware of the advertising and product	9.87	19.40
Preference (percent)	Average percentage of the people who like the advertising and product	9.20	54.10
Query volume (normalized 0~100)	Standardized number of the specific search keyword query volume	56.19	69.47

In addition, the data for the random utility model and the BLP correction method are as follow.

The analysis is based on 52 types of mobile phones, all of which were launched between 2008 and 2011. In addition, the analysis focuses on 3G (third generation) phones only, and therefore, excludes the so-called “3.5G or LTE (long-term evolution) phones.” The manufacturers of these phones include Samsung, LG, Pantech, Motorola, and Sony Ericson, among others. Collectively, mobile phone manufacturers launch approximately 50 new products each year in Korea. However, each manufacturer only has between three and five main models. Therefore, in this analysis, I use 52 kinds of 3G mobile phones. The 52 models were selected based on the monthly ranking published by Cetizen (www.cetizen.com), a well-known and influential mobile device community in Korea.

Data for the price and attribute variables were drawn for each of the 52 mobile phones. The price variable is the average retail price of a phone. When purchasing a mobile phone, telecommunication companies subsidize consumers. Thus, consumers do not actually pay the retail price of the phone. Instead, they pay a monthly rate, which includes the cost of device amortized over the period of the contract. However, the subsidy is calculated based on the retail price. Therefore, the average retail price of a phone is suitable. With regard to 3G mobile phone advertising, telecommunication companies emphasize WCDMA (wideband code division multiple access) services, such as video calls, and so on. The mobile phone attributes used here are whether the phone includes an MP3 player, whether it supports a touch screen, the type of DMB (digital multimedia broadcasting) service the phone uses, the phone's transmission speed, and the quality of the phone's camera. These variables are set as dummy variables. There are two types of DMB service, namely T-DMB (terrestrial DMB) and S-DMB (satellite DMB). The S-DMB is a charged service, and provides more channels than the T-DMB service, including international sport, and so on. Thus, the DMB dummy variable is set to 1 if the phone uses S-DMB, and 0, if it uses T-DMB. The transmission speed variable is set to the data transfer rate of the phone. The camera pixel quality and the transmission speed variables use the information specified in the phone's manual.

Strictly speaking, the device attributes and telecommunication service characteristics should be divided. However, in Korea, the phone manufacturers have a special relationship with the telecommunication service providers, which is a distinct characteristic of the Korean telecommunication market. Here, the specifications of a mobile device depend on the telecommunication service provider. For example, MP3 music players use proprietary DRM (digital rights management) formats, because each telecommunication service provider has its own music format. The DMB attribute also depends on the service providers. T-DMB is free, but the channel is limited. In contrast, S-DMB is a pay channel provided only by SK Telecom. In this study, the attributes used in the model analysis are appropriate.

The data set is composed of time-series data. Therefore, a stationary test must be conducted on the data set before the estimation. To examine the stationarity of the data, I first check the trends in the original data plot. Then, I conduct the stationary test on the data set using the ACF (autocorrelation function) and PACF (partial autocorrelation function). The results of the stationary test are presented in Appendix A. In addition, I conduct the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests as unit root tests on the data. The results of unit root tests are presented in Table 8.

Table 8. The results of unit root tests

	Augmented Dicky-Fuller test	**Phillips-Perron test**
	I(0)	**I(0)**
Sales	-6.210***	-6.367***
Advertising spend	-5.253***	-5.174***
Preference	-3.809***	-3.898***
Awareness	-6.006***	-6.010***
Query volume	-2.632*	-2.680*

※ Significant level: ***p<0.01 **p<0.05 *p<0.10

4.2 Estimation Results and Empirical Findings

- **Endogeneity and causal-relationship Analysis**

First, Table 9 shows the results from the simultaneous equation model estimation for advertising spend, awareness, preference, search query volume, and sales variables. The multi-collinearity of the independent variables before the estimation was examined because multi-collinearity can render the estimation results biased and cause an error. The correlation coefficients of the independent variables and the variance inflation factor (VIF) were reviewed to verify the absence of multi-collinearity in the data.

Table 9. Parameter estimates of simultaneous equation model

		Coefficient	Std. Error	t-value	Sig. level
Equation (3.1) (Sales)	Advertising spend	-297.59***	76.32	-3.9	.000
	Awareness	12183.27***	2841.82	4.29	.000
	Preference	8215.39***	2299.83	3.57	.000
	Advertising spend *(t-1)*	82.00**	35.57	2.31	.021
	Query volume	1753.89***	333.29	5.26	.000

Equation (3.2) (Ad spend)	Sales	.035***	0.004	9.91	.000
Equation (3.3) (Preference)	Advertising spend	.029***	.005	5.31	.000
	Awareness	.1.219***	.225	5.42	.000
	Advertising spend *(t-1)*	.008**	.003	2.89	.005
Equation (3.4) (Awareness)	Advertising spend	.015**	.005	3.15	.002
	Advertising spend *(t-1)*	-.002	.004	-.69	.488
	Sales	.001	.001	.99	.322
	Sales *(t-1)*	.000	.000	.86	.391
Equation (3.5) (Query volume)	Advertising spend	.037*	.019	1.96	.050
	Awareness	.003**	.0000	3.36	.001
	Advertising spend *(t-1)*	-.008	.008	-1.09	.277
	Sales	-.932	.863	-1.08	.280

※ Significant level: *** $p<0.001$, ** $p<0.05$, * $p<0.1$

The coefficients of Equation (3.1) show that all the independent variables, including advertising spend, awareness, preference, and query volume, are positive and significant to the sales volume. This result is consistent with the findings of previous studies that, generally, if a firm spends more on advertising, sales will increase (Tellis & Weiss, 1995). A number of factors influence sales. This equation uses key factors from the advertising sales response model and the communication model. Considering that the target of this analysis is the 3G telecommunication service, which is an intangible and vague concept, there are difficult concepts and technical terms associated with telecommunication technologies. Thus, consumers need a great deal of information about the products and services. In this case, advertising plays an important role in helping consumers to recognize new technologies and services.

For example, 3G telecommunication advertising strategically features a melodic and repetitive jingle and celebrities are used to endorse the products. This strategy encourages consumer recognition and brand preference. Finally, existing advertising measures of awareness and preference have a significant impact on sales increases.

In particular, the search query volume, the focus of this study, showed significant results, reflecting the consumer’s new behavioral pattern. This result implies that recent changes in consumer behavior influence purchasing decisions directly and indirectly. Generally, rational consumers know what they want, and seek to make the most of available opportunities, given the scarcity constraints they face. Therefore, consumers obtain information about a product before purchasing, and make a decision based on this information. This type of change in consumers’ behavior could appear in several ways. For example, studies on eWOM (electronic word of mouth) deal with internet services, such as blogs, SNS (social network service), and so on, and focus on the ripple effect of such services. However, current studies analyze internet search data generated by consumers' keyword searches. Search query data are generated promptly after a consumer conducts a keyword search. This means that keyword searches themselves could be a good measure of advertising effectiveness (Zigmond & Stipp, 2010).

In addition, "advertising spend *(t-1)*"—the lag variable of advertising spend at period *(t-1)*—that considered the carry-over effect was significant. As mentioned above, according to previous literature, this result shows that the carry-over effect of telecommunication services could be one month long (Choi & Varian, 2009; Han et al., 2009).

Equation (3.2) analyzes the relations between the advertising spend and sales. As mentioned above, advertising spend and sales have a positive relationship. This result proves that, in general, a firm's advertising budget is some portion of their total marketing budget. However, conventionally, the advertising budget is allocated in proportion to actual sales figures (Kwon & Koh, 2009).

Equation (3.3) shows that the more advertising spend, the more the preference. This result is consistent with that preference is influenced by advertising (Benhabib & Bisin, 2010). The advertising spend carry-over effect is verified because *(t-1)* advertising spend is significant at 5 percent. This result can be interpreted as follows. If the advertising spend increases, the number of advertisements increases or the advert is broadcast during prime time TV. Thus, consumers are exposed to advertising more easily, and their preference for the advertised product increases. In Korea, 3G telecommunication advertising caught consumers' attention by using a humorous story and the earworms inherent in commercial songs. Thus, these kinds of advertising factors make consumers' preference significant if advertising spend increases. Moreover, 3G advertising often has several episodes that form a story. Therefore, advertising broadcasted one month previously is still influencing consumers' present preferences. Therefore, the carry-over effect is significant.

In addition, the equation (3.3) awareness is significant. This results is supported by Homburg et al. (2010) who find that brand awareness significantly drives market performance (Homburg, Klarmann, & Schmitt, 2010). There are a few possible explanations for this finding. First, the awareness of product itself can affect preference because other consumers' product reviews are positive. If consumers recognize a 3G mobile phone and service, they might find several different reviews. For example, one consumer might be satisfied with a product, but someone else might not be satisfied. Thus, greater awareness is a sufficient condition for a higher preference (Yoon &

Kijewski, 1996).

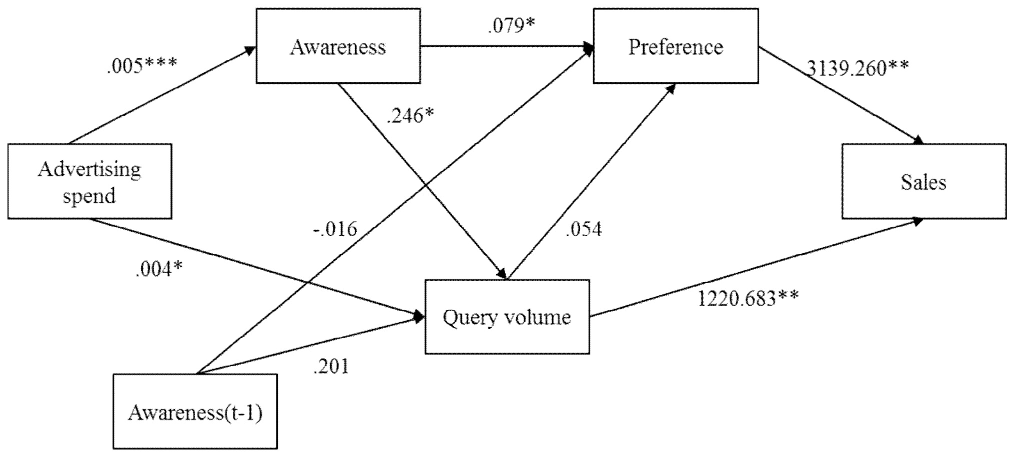
Equation (3.4) analyzes the variables affecting awareness, and the results show that advertising spend was significant at 10 percent. These results are identical to the result of equation (3.3) and can be interpreted from a similar perspective. Increasing the advertising spend played an important role in increasing the number of advertisements or in broadcasting during prime time. As a result, a positive image of the advertised product might become imprinted in consumers' minds. Finally, the awareness of 3G telecommunication services increases. These results are consistent with other findings on the effect of advertising on brand awareness (Clark, Doraszelski, & Draganska, 2009).

However, sales and *(t-1)* period sales lag variables are not significant. Thus, awareness depends on the advertising spend and sales (the number of new 3G subscribers) does not affect the awareness of the 3G service. Hypothetically, the sales variable was included because consumers who have already purchased new mobile phones could act as a form of advertising. However, this result implies that existing sold product might not influence potential consumer awareness.

Finally, in equation (3.5), advertising spend and awareness are significant to the search query volume, which implies that greater advertising spend and awareness compels consumers to search more. This results are consistent with Zigmond and Stipp (2010)'s study (Zigmond & Stipp, 2010). As mentioned, 3G telecommunication advertising uses various catchphrase and commercial jingles. The LG telecom advertising for the brand OZ incorporated storytelling and aroused consumer interest or curiosity (Maru, 2008). Therefore, consumers might search the Internet for information on the product after seeing it advertised on TV.

In addition, the equation (3.5), sales is not significant variable. In other words, the sales itself cannot affect search query volume because other consumers' word-of-mouth might not be influence to latent consumers.

Figure 28 shows the results from the path analysis model estimation for advertising spend, awareness, preference, search query volume, and sales variables. To take into account carry-over effects, the lag variable of awareness "Awareness *(t-1)*" is included.



※ Significant level: *** p<0.001, ** p<0.05, * p<0.1

Figure 28. Estimation result of path analysis

The results indicate that all the path coefficients of the advertising measure, except query volume to preference, awareness lag variable to query volume, and preference are significant. The variable "Query volume" represents consumers' interest in the product or service; however, query volume does not necessarily mean that consumers like the product or want to buy it. Therefore, the insignificant paths from query volume to preference and to sales are reasonable results, and the proposed model about the relationship of consumers' purchasing decisions with TV advertising measures is effective. Additionally, the path from the awareness *(t-1)* variable to the query volume is not significant. This result could be an indication that the consumer awareness response turn up promptly not after one month because 3G (third generation) telecommunication service and device are state of the art. Therefore, the awareness *(t-1)* cannot influence search query volumes at *t* period.

Also, the main focus of this study—that consumers' Internet search behavior is triggered by the TV advertisements, which are represented by the search query volume—is supported.

The chi-square value is a measure for evaluating overall model fit and, "assesses the magnitude of discrepancy between the sample and fitted covariances matrices" (Hu & Bentler, 1999). A good model fit would provide an insignificant result at a threshold of 0.05 (Barrett, 2007). While the Chi-squared test remains popular as a fit statistic, there are several severe limitations in its use. This test assumes multivariate normality, and significant deviations from normality may result in model rejection even when the model is properly specified (McIntosh, 2007). Moreover, because the chi-square statistic is sensitive to sample size it implies that the chi-square statistic almost rejects the model when large samples are used (Bentler & Bonnet, 1980; Jöreskog & Sörbom, 1993). On the other hand, when small samples are used, the Chi-square statistic is short of power, and so may not be able to discriminate between good models and poor models (Kenny & McCoach, 2003). Owing to the restrictiveness of the Chi-square statistic, researchers have sought alternative indices to assess model fit (Hooper, Coughlan, & Mullen, 2008). The root mean square error of approximation (RMSEA) is another fit statistic and was first developed by Steiger and Lind (Steiger et al, 1990). The RMSEA determines whether the fit of the model would fit the population covariance matrix with unknown but optimally chosen parameter estimates (Byrne, 2009). Until the early 1990s, an RMSEA in the range of 0.05 to 0.10 was considered an indication of fair fit, and values above 0.10 indicated poor fit. It was thought that an RMSEA of between 0.08 and 0.10 provided mediocre fit and below 0.08 was a reflection of good fit (MacCallum et al, 1996). However, a cut-off value close to 0.06 (Hu & Bentler, 1999) or a stringent upper limit of 0.07 (Steiger, 2007) appears to be the recent consensus (Hooper et al., 2008).

The test results of the path analysis model are presented in Table 10:

Table 10. Goodness of model fit of the path analysis model

Chi-square	Degree of freedom	Probability	RMSEA
5.857	4	0.210	0.099

Comparing the path analysis results to the results of the simultaneous equation model mentioned earlier, the estimated results are consistent. The simultaneous equation model assumes endogeneity and no direction within variables. In contrast, the path analysis model assumes that there is causality and direction within variables. In other words, the two models have fundamentally different assumptions. Nevertheless, the estimation results of two models are coincident.

In summary, from the two econometric models, the above estimates proved that awareness, preference, and search query volume have the causality in the effect of advertising sales response, and therefore the proposed models in this study are supported.

Finally, the strategic implications from the empirical analyses of the two models are as follows. First, all variables used in the simultaneous model are significant factors of sales increases. This result means that advertising could be an effective tool for promoting a new product or service, as well as increasing the sales of high-tech products or services, such as 3G telecommunication services. The 3G telecommunication service is a difficult concept for most consumers. For example, there are many difficult technical terms, such as WCDMA (wideband code division multiple access) systems. Therefore, the advertising should be easy to understand. The second strategic implication is that advertising spend affects awareness, preferences, and search query volumes. This result suggests that a greater amount of advertising spend has a significant ripple effect. Therefore, this result could be used to determine an optimal advertising budget allocation during advertising media planning.

4.3 Behavioral Model for Aggregate Demand and Consumer Preference

The estimation results of the BLP correction model are presented in Table 11. For the estimation, I use several variables, including product attributes generally used in random utility models, such as product price. Here, the product attributes are the key features of 3G mobile phones and services. In addition, I use the internet search influence variable and a measure of existing advertising. The internet search influence represents consumers' internet searching behavior before making a purchasing decision. In particular, this model uses the query count share of those people in a group of decision makers, n, who choose alternative i.

The multi-collinearity of the independent variables before the estimation was examined because multi-collinearity can render the estimation results biased and cause an error. The correlation coefficients of the independent variables and the variance inflation factor (VIF) were reviewed to verify the absence of multi-collinearity in the data.

Table 11. Estimation results of BLP correction model

	Coefficients				Collinearity Statistics[2]	
	B	Std. Error	t-value	Sig. Level[1]	Tolerance	VIF
Price	-.009 *	.0005	-1.76	.081	.7116	1.4053
DMB	.0857*	.0337	2.54	.012	.4956	2.0178
Speed	.0769**	.0381	2.02	.046	.1211	8.2554
Q share	.1248***	.0198	6.31	.000	.5603	1.7847
Awareness	.0107**	.0055	1.94	.054	.3790	2.6380
Preference	.0531***	.0092	5.77	.000	.1489	6.7140
Ad spend	.0109***	.0024	4.46	.000	.1541	6.4874
Ad spend *(t-1)*	.0047*	.0024	1.96	.050	.1927	5.1898

1) Significant level : *** $p<0.001$, ** $p<0.05$, * $p<0.1$

2) Collinearity Statistics: if the Tolerance ≤ 0.1 (VIF ≥ 10), multicollinearity exist.

First, the results show that the price, which is generally the most influential factor in consumers' purchasing decisions, is significant at the 10 percent level. As expected, price is the most important factor affecting consumers' choices. Among other variables including product attributes, DMB equipment and network transmission speed are significant at the one percent level. Specially, the DMB type variable is a dummy that takes the value 0 for T-DMB and 1 for SDMB. The result of the DMB coefficient is significant. This means that consumers prefer satellite digital multimedia broadcasting over terrestrial digital multimedia broadcasting. This is because S-DMB provides a greater variety of channels in addition to public TV programs.

The transmission speed of mobile phones is also significant. Three mobile service providers deployed massive advertising campaigns with respect to data communication and video calls when new services were launched. The advertising emphasized that the transmission speed of mobile phones is significant in network service choice and consumer might be affected by campaign messages on this topic (Maru, 2008).

Finally, the share of search query volume that represents the influence of Internet search query share to sales is significant at the 10 percent level. This implies that consumers who are exposed to TV advertising search for product information on the Internet and this behavior influences product sales (Zigmond & Stipp, 2010). This result could be a result of the complexity and unfamiliarity of new 3G mobile phones and services. Consumers seek information with respect to alternative reasonable choices. In addition, the instrument variable “advertising spend” is significant at the 5 percent level. Therefore, the hypothesis that search query volume might increase because of advertising is supported.

Awareness and preference, which are existing advertising measures, are significant at the one percent level. The results indicate that advertising effects have a positive impact on consumer choice of mobile phone service, both directly and indirectly. This is because the 3G advertising employed celebrities and employed easily retained commercial jingles to appeal to consumers.

To verify the reasonability of the estimation results, the elasticity of market share is calculated. The price elasticity of demand measures the rate of response to the quantity demanded because of a change in price. The formula for the price elasticity of demand is:

E = (percent change in quantity demanded) / (percent change in price)

Using price elasticity, it is possible see how sensitive the demand for a good is to a price change. The higher the price elasticity, the more sensitive consumers are to price changes. In other words, a higher price elasticity suggests that, when the price of a good goes up, consumers will buy a great deal less of it, and vice versa. A lower price elasticity implies the opposite; in other words, changes in price have little influence on demand.

The random utility model in the current study used the BLP method. Therefore, the dependent variable (the left side) of the model is the natural log-transformed market share.

The elasticity of the market share for each of the attributes is presented Table 12.

Table 12. The elasticities of market share

Attribute	**SKT**	**KT**	**LGT**
Price	-2.808	-2.011	-1.896
Speed	0.021	0.012	0.004
Q share	1.231	0.611	0.632
Awareness	2.277	2.932	2.948
Preference	4.566	3.865	2.348

First, the price elasticity of market share in all cases is elastic. This means that price changes of mobile phones trigger significant changes in demand. Thus, the market share of each telecommunication service provider changes elastically. This is a reasonable result considering the practical market at that time. In Korea, there are only three telecommunication service providers; thus, it is an imperfectly competitive market. In this case, if the performance and design of mobile phones are similar, consumers might be very sensitive to price. Moreover, the period for the data set used in this study was from 2008 to 2011. 3G telecommunication services began in earnest at the beginning of 2008. Since then, new subscribers have increased to 1,200 thousand, according to the competitive marketing of telecommunication service providers. In particular, the service providers have provided subsidies, as shown in Table 12. Most customers pay for the phone in installments, over the duration of the contract, rather than paying the retail price of a new phone. Moreover, this subsidy was at most 50% of the retail price of the phone. As a result, there were so-called “free mobile phones” because of the subsidy.

Table 13. The total amount of subsidy

(Unit : 100 million won)

	2007	**2008**	**2009 (the first half)**
SK telecom	4,395	8,980	5,282
KTF	3,539	5,986	2,468
LGT	1,264	2,669	1,777
Total	9,198	17,635	9,527

Source: www.ddaily.co.kr/news/news_view.php?uid=54824

Many consumers changed their second generation (2G) phone to a 3G-supported phone, according to the telecommunication service provider marketing campaigns. If the subsidy increases, the price of the mobile phone decreases, and the consumer reacts to the price change. Therefore, the price elasticity of market share is reasonable, and this result is consistent with previous literature (Kim & Kang, 2012).

Meanwhile, the change in market share according to the speed attribute is inelastic. This result means that consumers do not have utility with the transmission speed, because they cannot easily feel the data transmission speed.

With regard to the search query share, the change in the market share of SK Telecom is the only one that is elastic. This result could indicate that the amount of advertising spend affects the query share, because SK Telecom spent more on advertising than any other providers Finally, the change in market share according to awareness and preference are all very elastic. This means that the two representative advertising measures influence sales increases.

The scenarios for the sensitivity analysis use the six variables (i.e., price, speed, DMB, search query share, awareness, and preference) that were significant during the estimation. To examine the sales change because of a change in each variable, one variable only would have to change while others remain fixed. The range of price change considers the subsidy in the real market. As mentioned earlier, the subsidy reached a maximum of 50 percent of the retail price of the handset. The variable DMB is a dummy variable. Therefore, the scenarios include both dummy cases. Table 14 presents the ten scenarios.

Table 14. Scenario for sensitivity analysis

		Case A (DMB=1)	**Case B (DMB=0)**
1	Price	case A-1	case B-1
2	Speed	case A-2	case B-2
3	Qshare	case A-3	case B-3
4	Awareness	case A-4	case B-4
5	Preference	case A-5	case B-5

All the scenarios are applied to SK Telecom. However, KT and LGT did not provide satellite DMB. Thus, only the scenarios of case B are used for KT and LGT.

Table 15 shows the sensitivity analysis of SK telecom.

Table 15. Increment of market share of SK telecom according to the scenarios

Scenario	Case A-1 (price)	increment	Case B-1 (price)	increment	Case A-2 (speed)	increment	Case B-2 (speed)	increment
-50%	25.4	34.09%	26.7	19.24%	23.3	-0.02%	22.4	-0.02%
-30%	22.8	20.45%	25.0	11.54%	23.3	-0.01%	22.4	-0.01%
-10%	20.2	6.82%	23.3	3.85%	23.3	0.00%	22.4	0.00%
Base	19.0	-	22.4	-	23.3	-	22.4	-
20%	16.4	-13.63%	20.7	-7.70%	23.3	0.01%	22.4	0.01%

Scenario	Case A-3 (Qshare)	increment	Case B-3 (Qshare)	increment	Case A-4 (awareness)	increment	Case B-4 (awareness)	increment
-50%	20.1	-13.76%	19.2	-14.29%	22.8	-1.83%	22.0	-1.90%
-30%	21.3	-8.25%	20.5	-8.58%	23.0	-1.10%	22.1	-1.14%
-10%	22.6	-2.75%	21.8	-2.86%	23.2	-0.37%	22.3	-0.38%
Base	23.3	-	22.4	-	23.3	-	22.4	-
20%	24.5	5.50%	23.7	5.72%	23.4	0.73%	22.6	0.76%

Scenario	Case A-5 (preference)	increment	Case B-5 (preference)	increment
-50%	7.6	-52.84%	6.7	-55.88%
-30%	11.0	-31.70%	10.1	-33.53%
-10%	14.4	-10.57%	13.5	-11.18%
Base	23.3	-	22.4	-
20%	19.5	21.14%	18.6	22.35%

The sensitive variables in the scenarios are preference, price, and search query share. The increase in the market share according to the preference increase implies that the advertising effect influences consumer purchase intention. Additionally, this result supports the theory that search query share is a significant factor that represents the influence of other consumers on choice. The speed of a mobile device has minimal effect on a change in scenario. This result might be because consumers could not perceive the importance of the transmission speed of the mobile phone. Therefore, in marketing strategy, a firm must emphasize the concept of transmission speed to appeal to the consumer.

Table 16. Increment of market share of KT according to the scenarios

Scenario	Case B-1 (price)	increment	Case B-2 (speed)	increment	Case B-3 (Qshare)	increment	Case B-4 (awareness)	increment	Case B-5 (preference)	increment
-50%	28.2	10%	25.62	0.0%	23.7	-7.3%	25.4	-0.7%	12.3	-52.0%
-30%	27.2	6%	25.62	0.0%	24.5	-4.4%	25.5	-0.4%	17.6	-31.2%
-10%	26.1	2%	25.62	0.0%	25.2	-1.5%	25.6	-0.1%	23.0	-10.4%
Base	25.6	-	25.62	-	25.6	-	25.6	-	25.6	-
20%	24.6	-4%	25.62	0.0%	26.4	2.9%	25.7	0.3%	31.0	20.8%

Table 16 shows the sensitivity analysis of KT. The most sensitive variable with respect to scenario is preference. Once again, the speed of a mobile device has a minimal effect on scenario change. A noticeable result is that changes in market share according to preference are remarkable. This result corresponds to the real market situation. KT is second largest telecom company in Korea. Thus, KT's marketing campaign, the so-called "do the SHOW," improves consumers' preference for the brand, and thus, the firm's market share. This scenario indicates that changes in preference influence changes in market share.

Table 17. Increment of market share of LGT according to the scenarios

Scenario	Case B-1 (price)	increment	Case B-2 (speed)	increment	Case B-3 (Qshare)	increment	Case B-4 (awareness)	increment	Case B-5 (preference)	increment
-50%	23.2	12.8%	20.6	0%	18.1	-12.1%	19.5	-5.6%	11.3	-45.0%
-30%	22.2	7.7%	20.6	0%	19.6	-4.8%	19.9	-3.4%	15.1	-27.2%
-10%	21.1	2.6%	20.6	0%	20.1	-2.4%	20.4	-1.1%	18.8	-9.0%
Base	20.6	-	20.6	-	20.6	-	20.6	-	20.6	-
20%	19.6	-5.1%	20.6	0%	21.6	4.8%	21.0	2.3%	24.3	18.0%

Table 17 shows the sensitivity analysis of LGT. The most sensitive variable in the scenario is preference followed by the variable price. These results are very realistic. LGT's market share is the lowest of the three. When 3G telecommunication services were first launched, LGT was the last to enter the market. Furthermore, they used different a technology, the “CDMA EV-DO Revision A” system, to that used by SKT and KT, who used the “WCDMA” system. To increase their market share, LGT launched a new 3G service brand, “OZ,” and provided an open-mobile internet service. In addition, they reduced the price of their wireless internet service (http://www.designlog.org/2511322#.Uq0_K_RSYfE). As a result of these marketing strategies, consumers’ preferences, awareness, and search query might increase.

Chapter 5. Conclusions

The Internet has fundamentally changed the way consumers obtain information for purchasing decisions. The purpose of this study is to examine the influence of the internet searches on consumer purchasing decisions.

This study showed that Internet searches for product information influences purchase decisions, which marks a change in the consumer behavior pattern. TV advertising and the search query volume are closely related. Moreover, this study proposes an integrated model to analyze TV advertising sales effects along with changes in consumer behavioral patterns, specifically the consumer decision-making process, caused by exposure to TV advertising.

The current study shows that changes in consumer behavioral patterns should be considered in measuring advertising effectiveness. In terms of communication effects, the proposed model suggested a new consumer decision-making process reflecting the most up-to-date changes in the media environment, taking into account fundamental changes in consumers' behavioral patterns driven by the Internet search for information.

The estimation results proved that consumers' search patterns significantly influence advertising spending and sales volume, suggesting that changes in consumer behavioral patterns should be taken into consideration to measure advertising effectiveness. This approach could be a step toward understanding Internet searches' influence on consumers' purchase decisions. This study suggests using internet search data as a measure of consumer behavior and advertising effectiveness. Therefore, the significance of this study could be to initiate research in this field.

Changes in media driven by the increasing influence of new media, including the Internet and the introduction of new mobile devices, led to a new pattern in the consumer decision-making process. This study could be used to formulate companies' advertising strategies and government advertising regulations because consumers might base their purchasing decisions on Internet search results rather than TV advertisements.

As a marketing strategy, companies need to focus more on the consumers' behavioral changes and react accordingly with appropriate advertising strategies such as SNS (social networking service) promotions, cross-media marketing campaigns, and so forth. Companies need to remember that internet search influences people's purchasing decisions, and should use internet data when formulating an IMC (integrated marketing communication) strategy. In addition, media planning could use internet search data as a measure of consumers' response to the launch of a new product or service. By tracking trends in search query data, advertising could change according to consumers' responses.

In this way, a flexible attitude to advertising allocation could be possible, enabling advertisers to create effective advertising and thus meet their advertising goals.

In addition, ICT service companies could use internet search data when planning a new business. In particular, ICT services are closely related to internet searches, making search query data a major indicator of consumer interest.

On the other hand, the increasing influence of new media, especially Internet usage, hinders consumers because of information overload on the Internet or the exaggeration of product features. Consumers should not be misled by product information on the Internet and should strive to obtain correct information.

For example, the real-time ranking of keywords is popular. Most ICT service companies, such as Google, Naver, and Daum, provide such a service. Furthermore, the service has already become a topic of debate, as it is being abused by companies that tempt consumers to click on a keyword with the aim of making profits.

More recently, informative advertising has appeared. At first glance, this kind of advertising looks like information. However, the contents include advertising a specific product or service. Most consumers are not aware that the content is advertising, and so click on the contents to obtain more information. However, all they find is advertising. In more serious cases, these sites might be online scams such as phishing.

Another issue is that the prevalence of smart phones makes it easier to disclose personal information. Most users have several applications on their smart phones. These applications provide terms and conditions that the user is required to read before installing, but in reality, few consumers actually do so. This allows the service provider to mine personal information from the smart phone. Application providers gather information to use in marketing campaigns or new business development. In most cases, consumers do not know that their personal information has been taken from the phone, unless an obvious incident of abuse occurs, such as phishing.

Therefore, the government regulation authority should focus on advertising media and Internet service policy to protect consumers from Internet deception. They should make proper guideline for protecting personal information consistently according to the rapid change of internet environment. Also, the government authority should keep a close watch of a new type of swindling made by informative advertising in smart phone application.

Finally, it was difficult to consider a lot of variables that would verify the relationship between advertising effects and sales volume because the available data for the analysis were limited. The data constraint could be overcome by collecting more reliable data in the future. If the data can be identified from a consumer's demographic information, the sampling analysis in future research will be able to classify the purpose of a type of search.

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Appendix A: The Results of Stationary Test

1. Sales Data

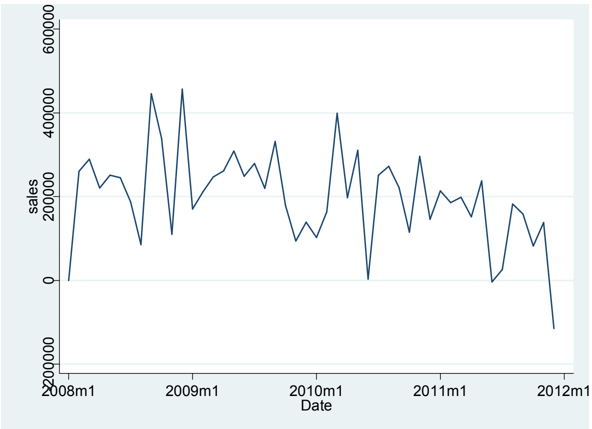

Figure 29. Original sales data

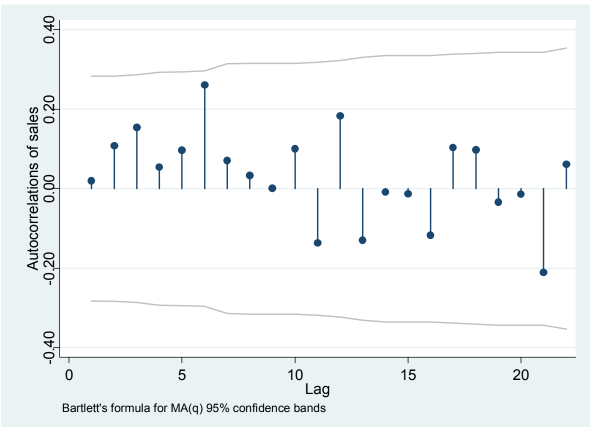

Figure 30. ACF of sales data

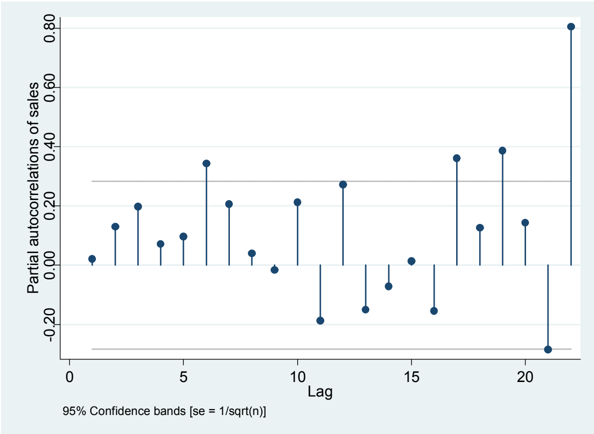

Figure 31. PACF of sales data

2. Advertise spend

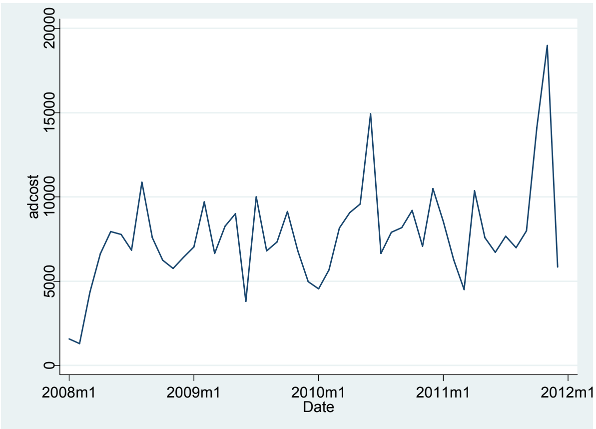

Figure 32. Original data

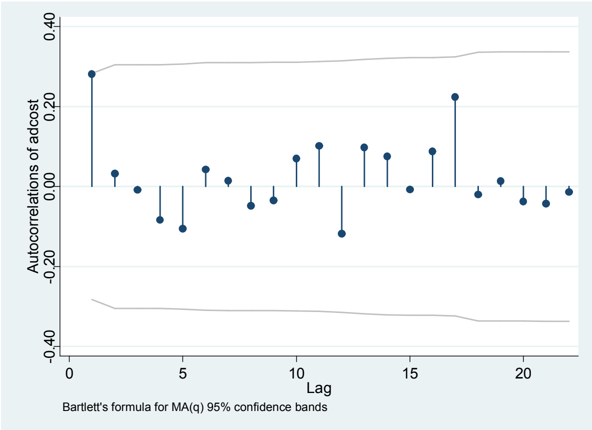

Figure 33. ACF of advertising spend

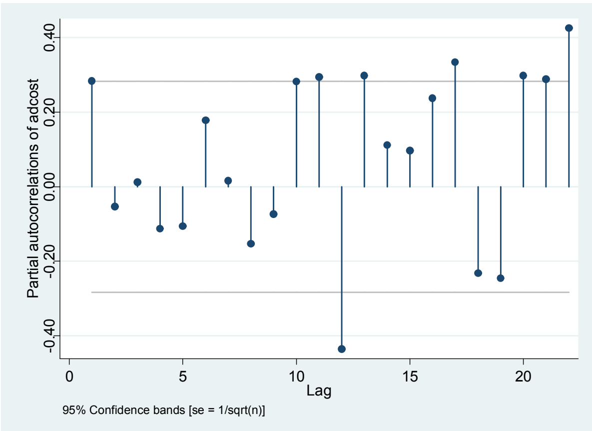

Figure 34. PACF of advertising spend

3. Preference

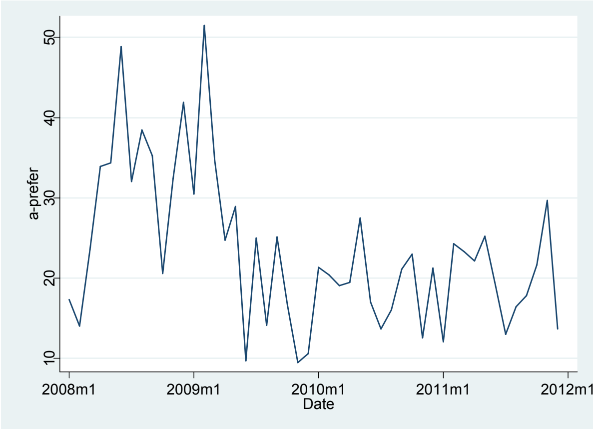

Figure 35. Original data

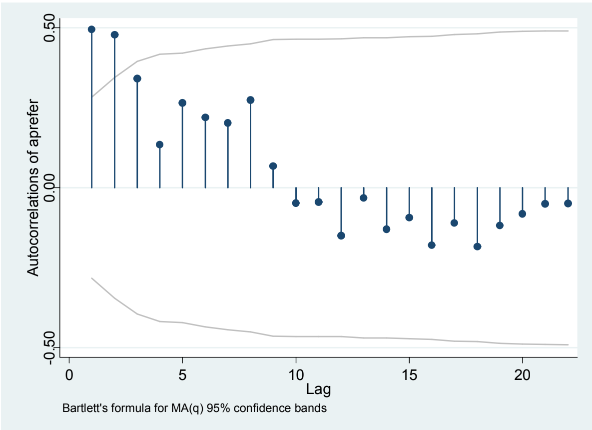

Figure 36. ACF of preference

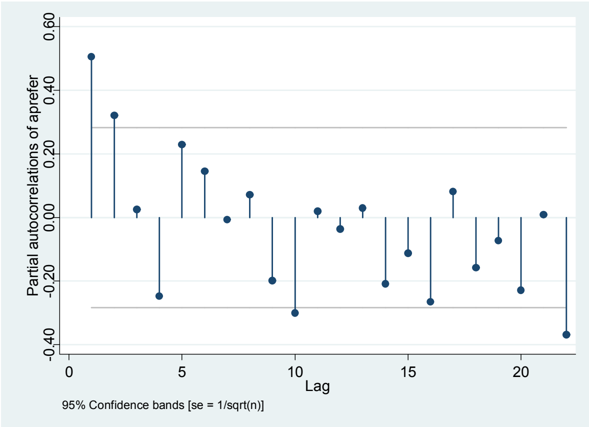

Figure 37. PACF of preference

4. Awareness

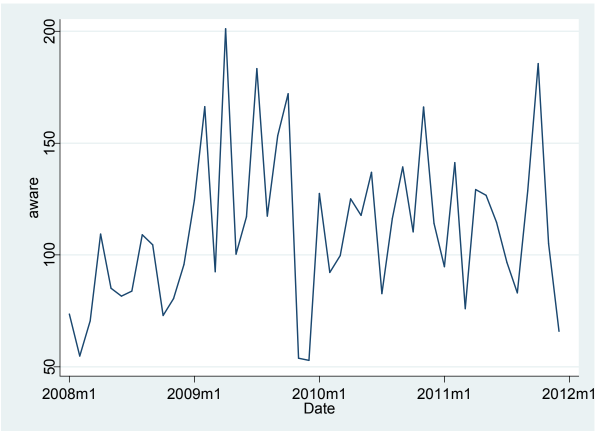

Figure 38. Original data

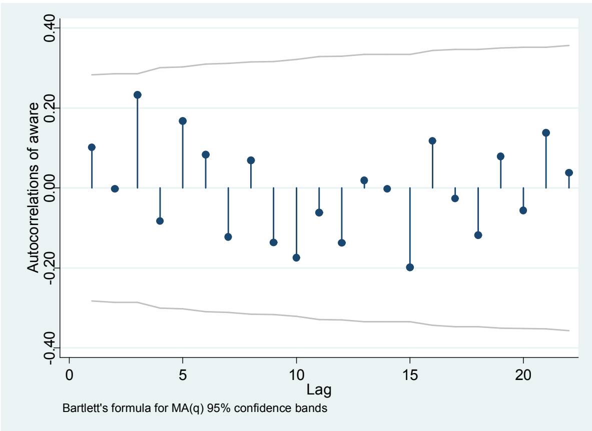

Figure 39. ACF of awareness

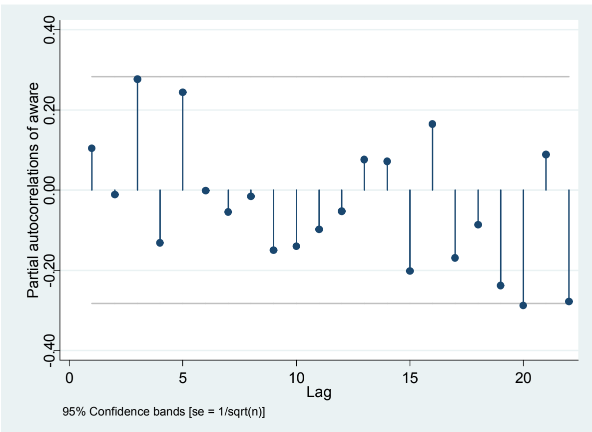

Figure 40. PACF of awareness

5. Search query volume

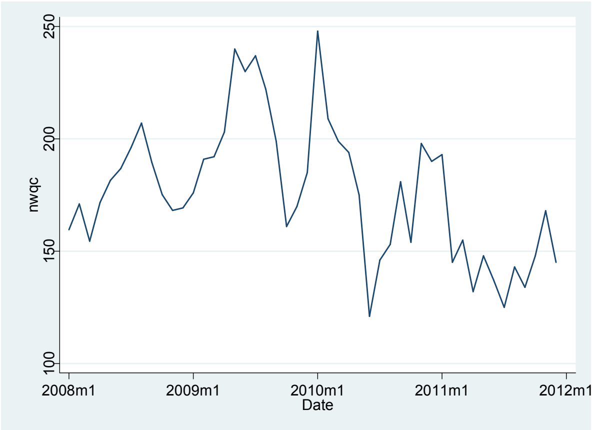

Figure 41. Original data

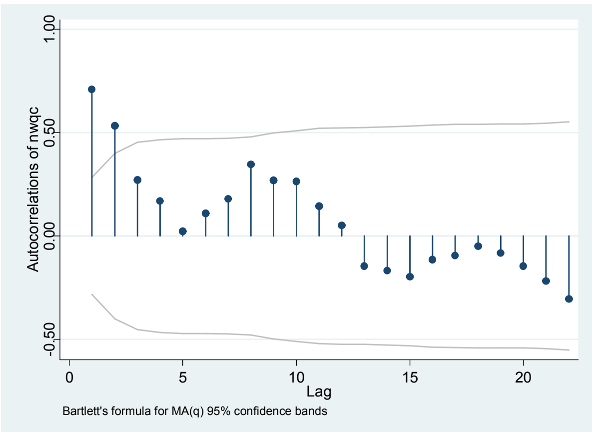

Figure 42. ACF of search query volume

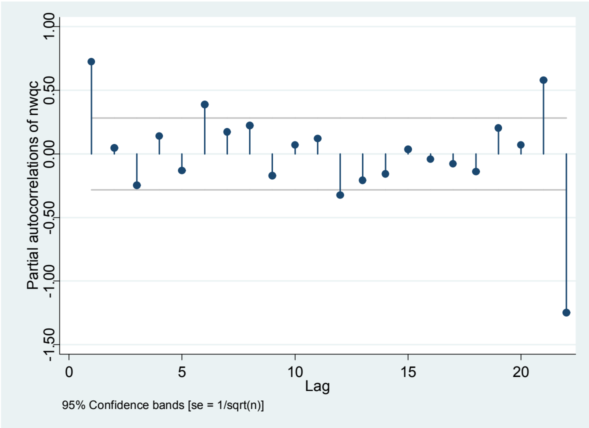

Figure 43. PACF of search query volume

Abstract (Korean)

본 연구의 목적은 소비자의 신제품이나 신규서비스 선택과정에 있어서 인터넷 검색의 영향력을 검증하는 것으로, ‘TV광고 시청 후 인터넷 검색’을 통한 상품정보 탐색 행동이 소비자 구매의사 결정에 미치는 영향을 실증적으로 분석하는 것이다. 이를 위해서, 본 연구에서는 소비자 구매 의사결정과정에 영향을 주는 TV광고 효과지표로써 인지도와 선호도를 활용하고, 또한 새로운 소비자의 행동변화 패턴의 결과 지표로써 인터넷 검색량 데이터를 사용하였다. 이러한 지표를 고려하여 광고 커뮤니케이션 효과 및 판매효과를 통합 분석하는 모형을 제시하였다. 연구에서 제시된 통합 모형은 소비자 의사결정 과정에서 TV광고 노출로 야기되는 소비자의 행동패턴 변화에 따른 TV광고의 판매효과를 세 가지 관점에서 분석하였다.

실증분석은 세 가지 관점에 따른 방법론에 의해서 이루어졌다. 그 중 두 가지는 연립방정식 모형 및 경로분석 모형이다. 이것은 다양한 광고효과 측정지표들이 가지는 내생성 및 인과관계를 검증하고, 분석하기 위해서 사용되었다. 나머지 방법론은 소비자 효용구조에 기반한 모형으로 인터넷 검색량 데이터 특성인 총합수준의 소비자 수요를 분석하기 위해서 사용되었다. 이러한 세 가지 모형들은 소비자 구매의사결정 단계에서 광고 효과를

나타내는 주요 지표들의 유효성을 검증하는데 활용되었다. 추정 결과 인터넷 활용으로 인한 소비자의 행동패턴 변화인 상품정보 획득을 위한 인터넷 검색이 구매의사 결정에 영향을 미치는 것으로 나타났다. 뿐만 아니라, TV광고와 인터넷 검색량 간의 밀접한 관계가 있음이 입증되었다.

위와 같은 개별 광고지표들의 유효성 검증은 소비자 구매의사결정단계에 있어서 광고효과 극대화를 위한 전략적 시사점을 제공해 준다. 또한 본 연구는 광고효과 측정에 있어서 인터넷 검색을 활용하는 소비자의 행동패턴 변화가 고려되어야 함을 보여준다. 이와 같은 연구는 소비자 구매의사 결정에 있어서 인터넷 검색의 영향력에 대한 이해를 한 단계 높이는데 기여할 것으로 판단된다. 마지막으로, 본 연구는 소비자가 TV광고 자체보다는 인터넷 검색 결과에 구매의사 결정을 많은 부분 의존하게 된다는 측면에서 기업의 광고전략, 정부의 광고 관련 규제 등 다양한 분야에서의 활용이 예상된다.

주요어 : 광고, 정보 검색, 소비자 의사결정 단계, 광고효과 측정 지표, 텔레비전
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