Abstract

This dissertation is intended to widen our understanding of three issues among IT-mediated phenomena observed after the revolution of social structure accompanied by the “paradigm shift”: (1) learning behavior of IT knowledge workers, (2) users’ consumption behavior of wireless communication services, and (3) consumer’s online shopping behavior, from the standpoint of research domain. For the perspective of research methodology, all four essays constituting the dissertation are developed based on an economic and econometric analysis. While the essays seem to be loosely tied together in either research methodology or research domains, they all aim to better understand the human intentional or adapted behaviors in everyday IT-driven socio-economic environment.

The first essay is entitled “The Learning Curve of IT Knowledge Workers in A Computing Call Center.” In the essay, by examining the basic nature of the learning curve in IT technical support services, I introduce two concrete concepts and measure the effects; new knowledge classification and IT problem types. I empirically examine the learning curve of the causal relationship between problem-solving experience and performance enhancement in a computing call center relying on both the econometric model based on traditional learning equation and a duration model.

The second essay entitled “Empirical Analysis of Mobile Voice and SMS service: A Structural Model” empirically examines the pricing effects on wireless telecommunication service demand based on an individual level. I, first, develop an analytical model to address consumers’ plan choices and optimal consumption under one-way and ‘step’ nonlinear pricing. Second, I utilize maximum simulated likelihood method to estimate the parameters specified in the model.

The third essay of “On Product-level Uncertainty and Online Purchase Behavior: An Empirical Analysis” is basically motivated by the fact that there are two kinds of uncertainty embedded in online shopping: (1) uncertainty relating to virtual retailers and (2) product-level uncertainty indispensably generated due to the omission of experiential information. Given that, I examine a product-level uncertainty reduction process in two dimensions: (1) product attribute (intangibility level) and (2) price.

The fourth essay is entitled “Trajectory-based Consumer Segmentation and Product Positioning in the Online Markets.” This essay again addresses online consumers’ shopping behavior. I identify the distinctive longitudinal shopping patterns (online consumer segmentation) on hypothesized consumer types and further suggest a practical framework for an optimal product positioning on an individual level using the trajectory based-segmented consumer groups.
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Chapter 1: Introduction

The past two decades have seen the amazing advancement of Information Technology (IT) and so one cannot consider life apart from IT or IT based-application, especially those embracing the current socio-economic evolution. Hardly anyone will disagree that the current socio-economic environment is a world suffused with ubiquitous, interdependent, and emergent IT. Furthermore, we (or future generations) may record the history of IT-based evolution as the revolution of social structure accompanied by the “paradigm shift” developed by Kuhn (1962), who developed several important notions in the philosophy of science. Given that, we will encounter bigger questions than both research questions shown and answered in academic literature, and agendas of industrial reports. That is “How did IT change the pre-existing world on the social-economic level and what is the outcome?”

Figure 1.1. IT-mediated worlds

From the point of view of social scientists in IT or economic discipline, we can answer the question by reflecting on the evolution of world proceeding over the contemporary generation based on (1) the advent of the on-line world that has outspread along with the popularity of Internet and (2) the change of the pre-existing structure of the off-line world. On the way of comparing the world deeply
embedded with IT to the pre-existing one, we find out that the “old” world has been extended toward three IT-mediated worlds as shown in Figure 1: (1) evolved off-line world, (2) augmented off-line world, and (3) newly created on-line world. This classification of worlds underlying the “new” paradigm is very intuitive. For example, the distinction between "on-line" and "off-line" has been conventionally seen as the distinction between computer-mediated communication and face-to-face communication. "On-line" is virtuality and "off-line" is reality (e.g. real life) (Slater 2002). However, there are so many relationships more complex than a simple "on-line" and "off-line" dichotomy. Consequently, even though we can understand intuitively that the three IT-mediated worlds show different facets to some extent, their boundary would be unclear. Furthermore, the ideas of "on-line" and "off-line" have been generalized from (easily observable) computing and telecommunication into the field of human interpersonal relationships, which is difficult to observe and calibrate (Slater 2002).

We can draw on the broad metacategories Orlikowski and Iacono (2001) discusses with respect to the IS research stream in order to make the practical distinction of the three IT-mediated worlds clearer. Seeking for the definition of IT or IT artifacts, they identify 14 specific conceptualizations resulting in 5 clusters based on the 188 articles published during the past decade of a premium IS journal (Information System Research). Their meta-analysis provides the primary conceptualization of IT that distinguishes each category: the tool view, the proxy view, the ensemble view, the computational view, and the nominal view. ¹ Their discussion is mainly oriented to IT itself but their classification would be helpful in clarifying the obscure discrimination of the three worlds with practical research topics.

¹ The computational view is mainly related to computational power of IT such as algorithm, information processing, and simulation. This view reflects the traditional computer science approach. This type of studies may be considered to be “micro” IT typed research, compared to “Macro” IT typed ones. The proxy view of IT is based on one or a few key elements that are understood to represent the essential aspect, property, or value of IT. Both are more focused on the technical view of diverse IT methods (e.g., human perception in proxy view and design of computational system in computational view).
1.1. IT-mediated three worlds

1.1.1. Evolved off-line world

The evolved off-line world represents the embodiment of change of the off-line world. According to Orlikowski and Iacono’s classification, the nominal view about IT artifacts illuminates the evolved off-line world very well. In the nominal view, IT or IT artifacts are not described, conceptualized or theorized – IT is essentially absent from the articles. Constituting neither an independent nor a dependent variable, IT is an omitted variable. Here, we can re-clarify the attribute of IT as an exogenous variable rather than simply being an omitted variable – i.e., IT is given as an uncontrolled variable. Considering the magnificent impact of IT on everything omnipresent, IT ends up with a close relationship with the pre-existing world, making IT the best suitable prefix to almost all terminologies in social (or business) area – e.g., IT personnel, IT planning, IT professionalism, IT outsourcing, and IT governance.

According to Orlikowski and Iacono (2001), the third largest view of IT is represented by the tool view at 20.3 percent of the articles. This cluster includes articles that treat IT as a relatively straightforward, unchanging, and discrete technical entity. The studies based on the tool view of IT examine how IT has influence on pre-existing systems such as information processing, productivity, social relations, and labor substitution – the researchers similarly think of IT itself as the primary independent variable that may cause, moderate, or mediate such outcomes. What matters most in these studies is the dependent variable, which is affected, altered, or transformed by the tool. What this view suggests is that tool-using humans and organizations can vary labor needs, increase performance, enhance information-processing capabilities, and shift social relations.

The above two views are differentiated by how IT is treated in the pre-existing world: (1) an exogenous variable out of research scope or (2) an independent variable in research scope. Wherever IT is located to in their research framework, those studies explore the changed phenomena derived by IT. This shows us the change (evolution) of the off-line world.
1.1.2. Augmented off-line world

Slater (2002) states that the distinction of dichotomy of on-line and off-line is "obviously far too simple". He also argues that even the telephone can be regarded as an "on-line" experience in some circumstances, and that the blurring of the distinctions between the uses of various technologies (such as PDA and mobile telephone, television and Internet, and telephone and voice-over-IP) has made it "impossible to use the term 'on-line' meaningfully in the sense that was employed by the first generation of Internet." In the same manner, we would perceive that the socio-economic change induced from the advancement of network or telecommunication is beyond the simple change in the pre-existing off-line world, making it an augmented off-line world. Actually many IS researchers have paid much attention to network or telecommunication – e.g., network optimization, network externality, telecommunication service, telecommunication market, telecommunication cost, telecommunication system design (Banker and Kauffman 2004).

One of the best examples of the augmented off-line world would be the provision of the mobile telecommunication service.

1.1.3. Created on-line world

The advent of Internet based on IT leads to the on-line world, where some online activity completely substitutes for off-line social-economic activity (e.g., on-line shopping, on-line game, and on-line theater). It is obvious that individuals can get a bigger surplus from these kinds of online economic activity simply because they have more options by being able to replace a certain activity, which they have been doing offline, with the corresponding online activity only if the cognitive cost from a broader choice is not so huge. Given that, one significant impact of IT would be the creation of the online world, which is a new social structure. The created online world corresponds to “embedded system” or new “social structure” in the ensemble view of IT by Orlikowski and Iacono (2001). It should be noted that the articles that Orlikowski and Iacono (2001) have grouped under the ensemble view represent the smallest cluster. Accounting for 12.5 percent of the total set of articles, this cluster is characterized as a system
embedded in a larger social context or as a social structure within a network of agents and alliances. They evaluated that this group occupied an unexpectedly low share and expected there would be clearly scope for more work to be done from an ensemble view. Consistent with their anticipation, after their research period (the decade beginning in 1990 and ending in 1999), research topics such as electronic commerce, virtual teams, globally-distributed work, new challenges to privacy and intellectual property rights, etc. have been highlighted.

I believe that if you are asked “what is the best example of the online world?” the answer could be online shopping.

1.2. Outline of the dissertation

This dissertation seeks to understand human behaviors in three distinctive research domains selected from three IT-mediated worlds, respectively: (1) IT knowledge workers learning behavior in the \textit{evolved off-line world}, (2) mobile users’ service selection behavior in the \textit{augmented off-line world}, and (3) online consumers’ purchasing behavior in the \textit{created on-line world}. Four essays constituting the dissertation are build on an implicit assumption that IT is an exogenous factor triggering new phenomena. As a matter of fact, this implicit assumption was made in many studies, where IT is either absent, black-boxed, abstracted from social life, or reduced to surrogate measures (Orlikowski and Iacono 2001). Namely, all these studies are far closer to the human-centered view rather than technology-centered view.

The four papers examine three ex-post facto phenomena. The first essay corresponds to the study with the nominal view. The paper essentially treats IT as existing, referring to it in passing as the context, motivation, or background against which to set examinations of phenomena, in particular, the appearance of IT knowledge workers (IT professionalism). The second essay is related to both the nominal view and the ensemble view. The third and fourth essays are more involved with an ensemble view. Given that, the studies attempt to understand how people behave in the newly created socio-economic environment drawing on classical social and economic theories.
The dissertation attempts to answer “How do users appropriate the social structures embodied in a given technology and with what outcomes?” or “What are the intended and unintended consequences of using a given IT?” in each research domain (see the table 1). These questions are informed by the structurational model (theory) (DeSanctis and Poole 1994; Orlikowski and Iacono 2001). With regard to the research methodology, every essay borrows the basic idea from econometric empirical methodology (some with analytical framework).

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Underlying basis:
IT is treated as an exogenous variable in all essays
There are the changes of the human intentional – active, voluntary – (or natural – passive –) behaviors in the IT-driven everyday socio-economic environment.

Table 1.1. The summary of four essays

This dissertation is organized as follows. Chapter 2 of this dissertation is my first research paper on knowledge management based on learning behavior of IT knowledge workers. Chapter 3 is my second research paper on mobile demand structure of Voice and Short Messaging Service (SMS). In chapter 4, I am analyzing online consumer purchasing behavior based on conjecture of the product level uncertainty, which was not reflected in previous models accounting for online shopping behavior. In chapter 5, I analyze developmental trajectory and build product positioning framework.
Chapter 2: The learning curve of IT knowledge workers in a computing call center

Abstract

In a number of organizations, IT support services are provided through computing call centers. IT support services have certain unique characteristics, such as (1) a rapid pace of evolution of information technology (IT) and (2) a wide variety of support requests and required knowledge to address them. Using data from a university computing call center, this paper empirically studies the learning curve relationship between problem-solving experience and performance enhancement in a computing call center. We find that (a) a computing call center demonstrates a slower learning rate (7.1%) than that of manufacturing firms (on average, 20%); (b) the learning rate of the group in charge of requests associated with surface-level knowledge about application is significantly faster, on average, than that of the group solving problems requiring in-depth technical-level knowledge, in terms of average resolution time (ART), by around 13%; (c) the variance of resolution times becomes smaller in only the group with application-level knowledge as the group accumulates experience; and (d) the cumulative experience gained with solving problems within a problem type leads to the reduction of ART in other problem types, suggesting that knowledge transfer across IT problem types occurs. The estimation of the learning curve contributes to the development of a theoretically grounded understanding of IT knowledge workers’ learning behavior. Such a theory and associated empirical estimates are of direct value in making operational decisions such as in staffing call centers.

Key words: Computing Call Center; Group or Organizational Learning; Knowledge Classification; Knowledge Transfer; Knowledge Management; Learning Curves
1. Introduction

The study of learning – of individuals, groups and organizations – is important as knowledge is a critical resource for competitive advantage for firms (Argote et al. 2003). In particular, as Information Technology (IT) technical services become increasingly important, we need a better understanding of learning in the context of IT technical support services. However, most previous work on learning has largely paid attention to machine- or labor-intensive industries, such as truck assembly (Epple et al. 1991), aircraft construction (Benkard 2001), and steel wire production (Lapre et al. 2000). In contrast, this paper focuses on learning by groups of IT knowledge workers in a computing call center.

Better understating of learning by IT knowledge workers is of value, from both a practical and a theoretical standpoint. From a practical standpoint, knowledge of learning behavior permits intelligent staffing and capacity planning in the presence of turnover and learning progress (Gans and Zhou 2002). Of more fundamental value is a theoretically grounded understanding of IT knowledge workers’ learning behavior – in particular one that accounts for IT knowledge categories and knowledge transfer between IT problem categories – with the “nominal view” of IT (Orlikowski and Iacono 2001).

Following an examination of more than 200 learning curve studies, Dutton and Thomas (1984) argued that learning rate should not be treated as a constant based on past experience, and emphasized the importance of contingency variables in predicting the learning rate. Following this line of thought, previous studies compared learning curves under various conditions (e.g., Lapre et al. 2000; Schilling et al. 2003). We propose a new knowledge classification – (surface-level) application-level knowledge vs. (in-depth) technical-level knowledge) and analyze its moderating effect on learning progress. The classification was motivated and developed based on the job classification of IT knowledge workers. There are several layers of these type of workers in service organizations (Das 2003; Gans and Zhou 2002). These workers are not homogeneous: different employees have different service capabilities in terms of required skill levels and/or knowledge types. Furthermore, individual service capabilities may change, depending on the required skill or knowledge, over time during the learning process. We examine
the learning progress of different groups in an organization, estimates of which have direct bearing on staffing in the dynamic environments encountered in IT call centers.

Further, we also investigate knowledge transfer within our specific setting. Knowledge transfer has been examined in diverse organizational contexts (Darr et al. 1995; Ingram and Baum 1997). Previous studies have mainly been concerned with knowledge transfer between organizations – i.e., they examine performance enhancements and their mechanisms when one group or organization transfers accumulated knowledge to another group or organization. Here, our approach is “microscopic,” as compared to the more “macroscopic” view. IT problems are categorized into multiple problem subtypes, such as networks, operating systems (OS), and so on. We conceptualize this configuration as the network of IT problem types and investigate whether experience accumulated on a single branch of the network has a positive influence on the problem solving performance in other branches. If it does, the positive relationship is attributed to knowledge transfer within the microscopic perspective.

The rest of this paper is organized as follows. §2 describes the research site. We develop the research hypotheses along with the conceptual background in §3 and describe the data in §4. Model estimation and empirical results are presented in §5 and §6. We conclude with the theoretical and managerial implications of our results and discuss limitations and future research directions.

2. Research Site

The research site for this study was a university computing call center. The center provides IT technical support services (problem solving) and information about computing to a university campus community. The center has been using the “Remedy system”2 since July 2001. It was introduced in May 2001 and implemented after a two-month period of testing and training. The data for this study covers the period from July 2001 through December 2004. The computing environment supported by the center is

2 Remedy system is a commercial system that is widely used to support call center services. It tracks calls for service and captures a variety of state information about a request thereby permitting visibility into the life cycle of a request. Remedy complies with ITIL, a service management standard. More information about Remedy is available at http://www.remedy.com/solutions/documents/misc/RMDY_ITIL.pdf.
heterogeneous along various dimensions. For example, operating systems (OS’s) range from HP OpenVMS and Solaris from Sun Microsystems to Microsoft Windows and Apple’s Mac OS. Requesters varying from naïve to expert have different depth of IT knowledge. Requesters can access the services of the center by walking in, calling on the phone, or by sending an email.

There are three types of consultants: Part-time student Generalist (PG), Full-time staff Generalist (FG), and Full-time staff Specialist (FS). The generalist group consultants (PGs and FGs) share the same office. A few FSs share a room with other FSs, but most FSs have individual cubicles. Technical support work is organized with PG, FG, and FS making up a problem-solving hierarchy with problems escalated when necessary (PG => FG => FS). A PG is responsible for problems in many fields (diverse problem types) requiring surface-level knowledge about applications (Chan and Bereiter 1997; Hayes-Roth et al. 1983; Turban 1995) and a FS solves problems requiring in-depth fundamental technical knowledge while specializing in a specific area such as network infrastructure. Consequently, specialists have deep fundamental knowledge underlying application-level knowledge (e.g., understanding “the IEEE 802.11 protocol stack” vs. knowing the settings under Windows to obtain wireless internet access) and are more likely than the generalists to find solutions to difficult problems.

Knowledge can be accumulated either from an investment in preparation and training (learning-before-doing) or through experience gained during actual implementation of relevant work (Carrillo and Gaimon 2000; Pisano 1994). In our research site, “learning-before-doing” projects have not occurred, except for on-the-job training for new consultants. That is, the level of cumulative knowledge was modified only through on-site learning. This represents an appropriate context for examining the learning curve induced from “learning-by-doing.”

In the process of verifying real operating procedures and data extracted from the Remedy system DB, we found that there were some procedures that were not formally documented, but which played a

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3 As to hiring part-time consultants (PG), the center requires a minimum of working hours per week (at least 6 hours or 12 hours a week depending on an academic session). So, even if they are part-time consultants, they have enough time to increase experience.

4 The hierarchical structure of consultants is similar to the research site of Das (2003) which also had three layers of consultants, and the hierarchical escalation of problems from one consultant layer to another.
critical role as solutions to user problems were developed. We compiled formal work processes as well as informal ones through intensive interviews with a manager and consultants at the site. One of the co-authors also spent several weeks at the center observing work and participating in solution seeking procedures of some problems. Here “informal” represents a work process that cannot be extracted from the DB, such as getting assistance from peers.

To better understand the work conducted at the center, we describe the three basic steps following a request sent in by a user: (1) problem report and preliminary action, (2) searching for solutions, and (3) closing the request by reporting the solution.

**1. Problem report and preliminary action**

In the first stage, a generalist (usually a PG), randomly picks up a request in the queue. When a request is opened, the request describes the problem reported by the requester. Based on the problem description, the consultant taking the request assigns a problem-classification code (CTI code) to the request and determines the criticality of the request. If necessary, in an email request, the consultant exchanges emails with the requester in order to better understand the problem.

**2. Searching for solutions**

This stage occurs when an IT consultant tries to solve the reported problem. A PG generally follows the solution searching procedure shown in Figure 1.

![Figure 1](fig.png)

After taking preliminary action, the PG tries to solve the problem independently with multiple available knowledge sources. One of the most critical knowledge sources is the Remedy system DB, which contains all the prior requests and their solutions. If the PG cannot solve a request with his or her

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5 CTI stands for Category, Type, and Item (e.g., Category: Web Services, Type: www.cmu.edu, Item: Server problems.) It is a hierarchical categorization developed to classify IT problem types. The set of codes has been updated over time. A predefined “criticality” is tentatively assigned to CTI codes. For example, “Network Restoration Requests” are always assigned to a criticality of 1 (Urgent). But the determination of criticality might partly be subject to an individual requestor’s situation.
individual knowledge, the PG will refer to the solutions of previously reported requests, using Remedy system as a second step. Hereafter, we will call this the “pseudo-working group,” since the repository is a compilation of previously seen problems and solutions developed by other consultants. If the PG cannot resolve the problem by him- or herself through either the “individual working” or the “pseudo-working group,” the PG will ask for help from other consultants. There are three actions that a PG can take to get assistance from other consultants: (1) consulting another generalist (PG or FG) through face-to-face discussion; (2) contacting a specialist through the instant messaging system without the change of ownership of the request; (3) escalating the request to FG (second-level generalist) or specialist (FS), along with the transfer of ownership of the request. The first and the second actions are comparable to “get help” and the third action is identical to “give away” in Pentland’s (1982) analysis of organizing moves of technical service interaction. The first approach of seeking help from the “real” working group on a problem is very common in the generalist group because they share the same office, even if a particular generalist holds the ownership of the request (refer to the upper diagram in Figure 2). The second approach is used when a PG wants to get the relevant information from a specialist. When the PG selects the second approach, he or she may already know who the most appropriate specialist to address the problem is. In other words, consultants have a well-developed transactive memory of who knows what (Lewis et al. 2005; Liang et al. 1995; Wegner 1986). However, it is extremely unlikely for a generalist to get assistance from a specialist without directly transferring the ownership of the request. 6 The third approach indicates the escalation of the request. Depending on the knowledge types required to solve the request, a PG will escalate the request to either an FG or an FS, along with the ownership of the request (refer to the second and third diagram in Figure 2). As shown in the third diagram, when an FG cannot solve a problem, the FG escalates the request to the corresponding full time specialist, FS. Figure 2 shows the workflows depending on the request ownership change, where the circle drawn with a dotted line describes “real working group.”

6 We cannot measure exactly how rare this case is because it is an informal work process and so it was not officially recorded. We interviewed generalists and found that the possibility of consulting specialists without the change of ownership was less than 1%. 

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(3) Closing the request by reporting the solution

If the answer for a reported request is acquired through one of the procedures described above, the consultant with the ownership of the request classifies the request as closed after obtaining confirmation that the requestor is satisfied with the solution. In the dataset, every request is matched to one consultant, who gives the final solution to the requester irrespective of whether the request was solved by an individual working or by a group working together. Once a request is closed, all actions associated with the request, including solutions, are stored in one field of the Remedy system DB (i.e., added to the knowledge repository) to facilitate potential reuse in solving similar problems (refer to the “Pseudo-working group” in Figure 1).

3. Conceptual Background and Research Hypotheses

Although there is a large body of literature on learning curves, a complete theory of learning in the context of IT technical support services does not exist (Das 2003). We develop a set of hypotheses pertaining to learning in our problem-solving context along with a review of learning theory literature and a discussion of how we apply it to our setting.

3.1. Learning Curves in a computing call center

With end-user computing environments that have proliferated since the 1980s (Bergeron et al. 1990), computing call centers have been established in a majority of organizations. When we apply learning theory to the IT knowledge working environment, we need to attend to the uniqueness of both the IT environment and the corresponding IT knowledge pool required to solve reported IT problems. First of all, rapid IT advancement results in a “high-velocity” IT environment with upgrades, newer versions, or completely new artifacts. This extremely dynamic environment has been shown in previous studies to occur on the IT industry level as well as with specific IT application artifacts. The rate of
change in the IT industry environment documented through diverse measurements such as “product life cycle,” “freshness” of the product line, and clockspeed far exceeds that of other manufacturing industries (Mendelson and Pillai 1998; Mendelson and Pillai 1999) – refer to Figure 3 in Mendelson and Pillai (1998) for the comparison of the metrics between IT industry and other industries. For example, in the specific domain of database management system (DBMS), we can trace the evolution in database technology in terms of the data model (Navigational DBMS => Relational DBMS => Object-Oriented DBMS => Object Relational DBMS => eXtensible Markup Language (XML) DBMS) and in the query language (procedural query language, structured query language (SQL), XML query language (XQL)) supported. Further, the suppliers of IT hardware and software are diverse and the ultimate IT systems are made up of several components, which include microprocessors, motherboard, DRAM, chip sets, peripherals, PC systems, networks, operating systems, Office suites, and application software (Kraemer and Dedrick 1998). The large number of combinations may require correspondingly different knowledge pools, due to technical compatibility problems and the lack of complete standardization. While computing end users can focus on a small part of the large set of options available, IT technical supporter providers are required to be acquainted with all elements in the set because they confront diverse IT end users using different combinations. Therefore, not only are IT technical service providers faced with a large knowledge pool induced from the many combinations of components, they also have to keep up with the pace of rapid IT technology advancement.

Some might postulate that the learning rate of IT technical service providers is too slow to be observed, and that the interaction of a dynamic environment and large knowledge pool might especially prevent IT consultants from showing better performance through learning-by-doing experience gains. However, the opposite prediction might be supported with logic based on Ellis’s (1965) knowledge classification. According to Ellis (1965), learning can be subdivided into two categories: (1) content knowledge and (2) knowledge regarding learning how to learn. Focusing on content knowledge, if the content knowledge accumulated through previous experience is relevant to the content knowledge in a new knowledge pool evolved based on technology advancement, IT consultants will show a learning
curve characterized by performance enhancement. The second category represents learning associated with how to assimilate or apply particular kinds of information to the new problem, which enhances the logical thinking process. Learners may be able to apply logic developed in one problem to another problem, increasing their understanding in a problem domain and resulting in the “Aha!” experience of insightful problem solving (Gick and Lockhart 1995; Schilling et al. 2003). The knowledge accumulation in the second category is not susceptible to changes in the knowledge pool or the large size of the knowledge pool. Given these competing forces, it is not clear whether learning curves will be observed for IT knowledge workers in a computing call center – which leaves us with an interesting empirical question. Based on two performance measures (to be discussed in detail later), we hypothesize:

Hypothesis 1_1: As organizational experience in a computing call center increases, the organization will improve its performance as measured by – (1) shortening of average resolution time and (2) reduction of the variance of resolution times in unit time.

Hypothesis 1_2: Given the dynamic and wide ranging nature of IT knowledge that a computing call center requires, the performance enhancement in a computing call center (shortening of average resolution time) induced from previous experience will be slower than that shown in other industries (on average 20% from Dutton and Thomas (1984)).

3.2. New Knowledge Classification and Its Moderating Effect

The learning model has been applied to diverse units of analysis: individual, group and organizational levels (Reagans et al. 2005). The first set of hypotheses are focused on the organizational level, assuming implicitly that the multiple groups that make up the organization will not show significantly different learning curves – but this assumption may not be warranted. As we discussed, the computing call center of our research site is composed of three consultant groups (two generalist groups and a specialist group). The classification of “generalist” and “specialist” in IT technical service pertains to the depth of knowledge required by each group rather than the width of the related domains (topics) (refer to the online appendix for a more detailed discussion of generalist and specialist).
As IT has become ubiquitous (Carr 2003), one may subdivide IT knowledge into two sets: (1) surface-level application knowledge that everybody possesses to use IT for practical purposes, and (2) the more fundamental and detailed deep knowledge that goes beyond the simple usage of IT. For example, users can forward an email only if they know how to use a specific function of email client software such as “email forwarding” in Outlook Express. They don’t have to know the technical details of how this operation is implemented or executed. Users may be able to scan and remove computer viruses with anti-virus software such as ‘Symantec Antivirus’ even if they don’t know how vaccines work. Knowledge about “the network configuration of the email host computers,” “file transmission protocols,” or “how anti-virus software works” is more technical and fundamental than surface-level application knowledge.

The new classification of IT knowledge based on “where IT knowledge is used and at what level” is comparable to IT consultants’ job classification that we observe in our site. While generalists are responsible for a wide range of problem types, they are responsible for application-level knowledge (e.g., how to forward an email). In contrast to generalists, specialists are required to have and use underlying IT technical knowledge such as “network configuration.” Specialists focus on a narrow range (one or two) of problem types because of the inherent complexity of these types of knowledge.

In our site, PGs are responsible for requests that require application-level knowledge, and FSs are in charge of requests that require underlying technical-level knowledge. FGs fall between the two groups – they tend to have more technical knowledge than PGs and less than specialists. We examine whether these different groups follow different learning curves by testing the moderating effect of the surface-level application vs. the in-depth technical-level knowledge classification on the learning relationship.

The direction of the moderating effect (the relative difference of learning rates) can be predicted in diverse ways. First, reflecting on the attributes of surface-level and in-depth knowledge, we expect that surface-level application knowledge learning (building) would have more internal knowledge spillover – internal knowledge spillover is positive learning or knowledge externalities (Adams 1990; Argote and Ingram 2000) –, and thus learning about one function on application-level knowledge would yield better

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7 We tested the match between both classifications with consultants at our research site and received their affirmative assessment.
insights into how other closely related functions might work. For example, if you come to learn how to forward an email, you are highly likely to either learn other functions such as “find people” or “address book management” or understand the relevant tools as well as their structure. In contrast, learning of in-depth technical-level knowledge might not lead to the similar kind of spillover learning during relatively short time periods. Second, we try to compare our knowledge classification being operationalized from IT consultants’ job classifications with several previous knowledge classification (Anderson 1995; Ellis 1965; Hayes-Roth et al. 1983; Nonaka 1991; Polanyi 1958; Turban 1995). Although we might not make seamless matches, application-level knowledge is closer to “explicit knowledge (Nonaka 1991; Polanyi 1958),” “content knowledge (Ellis 1965),” and “surface knowledge (Hayes-Roth et al. 1983; Turban 1995)” while technical-level knowledge may be located more near the counterpart of the knowledge types (i.e., “tacit knowledge” and “logical thinking process knowledge,” and “deep knowledge”). Previous studies did not explicitly investigate the different learning rates depending on the previous knowledge classifications. However, they enable us to conjecture that when compared to simple content and explicit knowledge, the acquisition of tacit and deep knowledge requires relatively many experiences or a long period of time such as a decade of intense study for acquiring a particular domain of knowledge (Hayes 1949) and approximately 50,000 “chunks” of experience in a chess game (Simon and Chase 1973). Third, because much application-level knowledge is involved in information about “know-how” rather than “know-how-implemented,” one may access and acquire fully understandable application-level knowledge through the widespread use of networked information resources (or the Internet) more easily than technical-level knowledge. For instance, in contrast to the easily accessible well-documented materials on forwarding in email client software, it is difficult to find the solution to problems presumably coming from the wrong implementation of a computer networking protocol suite.

Here, we aim to compare the learning progress of IT knowledge workers based on the theoretically hypothesized difference.
Hypothesis 2: The learning rate of the group in charge of requests associated with application-level knowledge will be significantly faster than that of the group solving problems requiring technical-level knowledge.

3.3. Knowledge transfer across IT problem types

Accumulated experience can be either heterogeneous or homogeneous (Haunschild and Sullivan 2002). In the case of heterogeneous experiences, we can conceptualize them as separate branches of a network. This conceptualization is based on the assumption that the knowledge sets every IT problem type requires are not identical but partly interdependent. That is, we can express the relationship between the problem solving experience of problem type “A” and problem solving performance of problem type “B” using a network with nodes indicating each problem type and links representing interdependencies.

Reflecting on IT consultants’ knowledge accumulation process, the heterogeneity of experience is comparable to problem-solving experience in different IT problem types. In our research site, the problem-classification codes (CTI codes) that IT consultants have used during the research period numbered about 1200. We used the CTI codes to create the IT problem type classification shown in Table 1. First, we sorted IT problem types from the computing end-users’ perspective, referring to Lee et al.’s classification (1995). Second, we classified every CTI code within a problem type sorted in the first step (refer to the online appendix for a more detailed discussion of IT problem type classification.)

<Insert Table 1 about here>

IT problems are expected to be mutually related to each other, in terms of knowledge accumulation and its influence on performance. For example, even if one IT consultant specializes in only virus problems or OS problems, he or she can gain knowledge in the network area by solving problems such as “virus attacking network port” or “OS setting pertaining to a network configuration.” Further, the anticipation of positive mutual influence can be rationalized on the “related variation effect.” The experience from diverse heterogeneous problems leads to better performance because of better understanding of latent schema by facilitating the development of more abstract principles (or schema)
related to a general class of tasks (Jehn et al. 1999; Schilling et al. 2003). That is, even if a consultant solves problems other than network problems, the consultant’s experience gains in other areas (e.g., OS or virus problems) may have indirect positive influence on performance in the focal area (e.g., network problems), by increasing the understanding of the IT knowledge pool, itself. Given that, we hypothesize:

**Hypothesis 3:** The cumulative experience with solving problems in a problem type will lead to performance enhancement (shortening of average resolution time) in other problem types, providing evidence of knowledge transfer across IT problem types.

4. Data

The data for this study range from July 2001 to December 2004. During the time horizon, there were 147 consultants, and more than 170,000 requests were resolved in the center. Data for our analysis were extracted from the Remedy system DB, where we obtained the information associated with the formal process: (1) a request ID, (2) a consultant ID finally reporting the solution to a requestor, (3) request created- and resolved-time stamps, (4) CTI code indicating the problem type associated with a request, and (5) criticality of a request. In particular, one field of the DB is the “request trail” that enables us to observe all formal actions that are taken by consultants before closing a request. The symbols used throughout the paper and the variables they represent are listed in Table 2.

<Insert Table 2 about here>

4.1. Dependent Variable (Performance Measurement)

We use two measures of productivity in technical support work: (1) average resolution time (ART) and (2) variance of resolution times in the unit of time (week). The first is very popular in measuring service performance (Das 2003; Zeithaml and Berry 1990), while the latter is proposed in this study. ART in week $t$ is the average of resolution times of all requests resolved in week $t$, where resolution time (RT) is the elapsed hours through the operation hours of the center between the first
reporting of a problem and its resolution. There are two reasons why resolution time is an important measure of the productivity of technical support services. First, the labor cost of knowledge workers occupies the majority of total cost for call center service. Second, customers’ assessment of services is strongly affected by the resolution time (Zeithaml and Berry 1990). This is especially true in situations where the time that requestors spend waiting for a solution represents a stoppage of work with consequent financial loss (Das 2003).

The other performance measure is the variance of resolution times of all requests resolved in week $t$. This is developed as a surrogate variable for stable and consistent accomplishment of work. Surprisingly, even though the concept of consistent problem resolution was introduced in prior literature (El Sawy and Bowles 1997), this metric has not been used in previous empirical studies for a performance metric. We use this metric as another measure of productivity of knowledge workers.

Performance variables are measured based on the requests only through “email” because we found that there were significant input errors regarding request created-time stamps in the other request methods (e.g., phone consultation and walking-in). When a consultant receives a request by phone or walk-in, he or she is likely to input the request created-time and resolved-time at the same time when the task is finished. Both request created-time and resolved-time are accurate when recorded through email, because the created-time is automatically recorded when an email request reaches the center and a consultant records the resolved-time when he or she sends the answer to the requester. As shown in Table 3, requests through email account for well over the majority of the requests (69.2%).

<Insert Table 3 about here>

4.2. Learning Variables (Knowledge accumulation proxy variables)

Our study was motivated by a desire to understand IT knowledge workers’ learning progress.

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8 We measure RT with two time stamps: Tc: request-created time and Tr: request-resolved time, $RT = Tr - Tc$. This is a proxy for the real time consumed to solve a request. There are three kinds of measurement errors between RT and “real resolution time”. But, the unobservable measurement errors do not affect our main analysis result, in particular, the slope coefficient of learning curves (refer to the online appendix).
Because our data contain the information regarding the consultant with the ownership of every request, we considered analyzing learning curves on an individual level. Given a group working environment, however, one cannot attribute performance improvement directly to individual learning, because consultants informally talk to other consultants (refer to the dotted circles in Figure 2). When we estimate individual learning rates based on our dataset, we cannot exclude the influence of assistance from other consultants. In addition to this real working group, individual consultants can refer to the solutions of previous requests documented in the Remedy system DB, which is not comparable to individual level knowledge accumulation (pseudo working group in Figure 1). Therefore, the estimation of the individual level learning rate may lead to biased conclusions due to our inability to control for peer effects. For this reason, we set the unit of analysis as a group-level learning curve.

Our research site shows a unique group structure. As shown in the left diagram of Figure 3, there are no fixed sub-groups (teams) that always work together in the generalist group. In a specific time period, a generalist group is composed of a few FGs and several PGs. The composition of the sub-group varies from time to time. Information on member composition and on the performance of each sub-group is not available. This implies that group composition would be an omitted variable in a regression model for estimating group-level learning curves. However, the group-level learning model can be estimated in an unbiased manner when (1) the influence (assistance) of an individual consultant on peers is proportionate to the individuals’ experience, and (2) the total cumulative experience in every subgroup is relatively invariant. Both assumptions are supported by the operating procedures at the center. The first is warranted because individuals who are more experienced have more knowledge and are more influential. The second is sustained by two features of the sub-group configuration: (a) sub-groups are randomly constructed according to individual PGs’ schedules, and (b) the most experienced consultants (FG) are always involved in almost all subgroups.

One of our research objectives is to examine the difference in the group performance improvement induced from experience. We can distinguish between three scenarios in Figure 2 which
enables us to compare learning curves of the different working groups. The learning variable is the cumulative request volume at time $t-1$ through all the methods to access the center, because consultants gain experience irrespective of the type of consult (phone, walk-in or email) and the accuracy of time stamps for measuring resolution times is irrelevant (recall that performance variables are measured based on the requests only through “email” in order to accurately measure a resolution time.)

5. Data Analysis

We analyzed the data based on two kinds of econometric model specifications: (1) a standard learning curve model and (2) a survival model. We will present and compare the results from both specifications in the next section. Here we describe the model specification based on the learning equation (refer to the online appendix for the details of the model specifications for the survival analysis.)

\[
\ln(RT_i/q_i) = \beta_0 + \beta_1 \ln(Q_{t-1}^s) + u_i
\]  

(1)

\[
\ln(RT_i/q_i) = \beta_0 + \sum_{s > 0} \beta_0 s D_s + \beta_1 \ln(GQ_{t-1}^s) + u_{ij}, \text{ where } D_1 = \text{FG} \text{ and } D_2 = \text{FS}
\]  

(2)

\[
\ln(RT_i/q_i) = \beta_0 + \sum_{s > 0} \beta_0 s D_s + \sum_{h > 0} \beta_1 h D_h \ln(GQ_{t-1}^s) + u_{ij}, \text{ where } D_0 = \text{PG}, D_1 = \text{FG}, \text{ and } D_2 = \text{FS}
\]  

(3)

These three models have two objectives. One is to estimate the organizational (model 1) or group (model 2 and 3) learning effect. The second is to compare three learning curves by consultant groups. In model 1, if $\beta_1$ is statistically significant and negative, then the overall organizational performance improves as it gains experience by solving more problems. In the second model, we include group dummy variables (we omitted the PG dummy to avoid over-specification.) If $\beta_1$ (negative sign) and $\beta_0 s$ (regardless of the signs) are significant, then the groups show significantly different initial ART’s, respectively as well as the group learning effect. In model 3, we include not only group dummy variables, but also the interaction terms between each group and the cumulative number of requests solved in the corresponding group, essentially splitting the data into 3 samples: PG, FG, and FS. We can test whether group classification (equivalently, new knowledge classification) influences (moderates) the learning rate in terms of both the intercept and the learning progress slope.
\[
\ln(Var(RT_{ij})) = \beta_0 + \beta_1 \ln(Q_{j-1}) + u_{ij}, \text{ where } j=0,1,2
\]  
(4)

\[
\ln(PT_{ij} - RT_{ij}/PT_{ij} - q_{ij}) = \beta_0 + \sum_{x=1}^{\beta_{0x}} PT_{x} + \sum_{h=1}^{\beta_{1h}} PT_{h} \ln(PT_{h} - Q_{0-1}) + u_{ij}
\]  
(5)

\[
\ln(PT_{ij} - RT_{ij}/PT_{ij} - q_{ij}) = \beta_0 + \sum_{x=1}^{\beta_{0x}} PT_{x} + \sum_{h=1}^{\beta_{1h}} PT_{h} \ln(PT_{h} - Q_{0-1}) + \beta_2 \ln(GQ_{0-1}) + u_{ij}
\]  
(6)

where \( PT_x \) and \( PT_h \) = 1,2,3,4,5; Virus, Network, OS, Email, Account

In model 4, we regress the variance of resolution times on the cumulative experience of every group, and compare the learning curves in similar fashion to model 3. In model 5 and 6, we split the entire data set into six samples (virus, network, OS, email, account, and others) based on the predefined IT problem type classification. In model 6, we add total cumulative requests in all problem types in addition to the cumulative requests in each problem type. This enables us to assess the knowledge transfer across IT problem types. Specifically, we check whether \( \beta_2 \) is significantly negative and the change of \( \beta_{1h} \)'s from model 5 to model 6. Because our concern is the relationship across IT problem types and specialists are focused on a specific area, we cannot empirically examine the issue of knowledge transfer in the specialist group. Thus, models 5 and 6 are estimated using data from only the generalist group.

6. Empirical results

We found significant autocorrelation in the residuals at the significance level 0.01 on the organizational level analysis (DW d-statistic (2,177) =1.037, \( d_k=1.598 \) and \( d_i=1.651 \)). The scatterplots of the residuals in each group were also examined, and they did not indicate heteroscedasticity. The null hypothesis of “constant variance” cannot be rejected at the significance level of 0.05 in both the Breusch-Pagan / Cook-Weisberg test and the White's test for heteroscedasticity in each group. As shown in Table 4, each group, however, has a different error variance (refer to the online appendix about why this occurs.) The data structure for models 1 and 4 is a time series, and the data structure for models 2, 3, 5, and 6 is a cross-sectional time series data (panel). We estimated models 1 and 4 with the ARIMA(1) model using maximum likelihood estimation. We fit the other models using FGLS (Feasible Generalized
Least Squares), which allows us to estimate the models in the presence of autocorrelation within panels, and cross-sectional correlation and heteroscedasticity across panels.

<Insert Table 4 about here>

As shown in Table 5, model 1 shows a significant and negative coefficient for the cumulative experience variable (-0.107, p<0.001), indicating that overall, the organization demonstrates a significant learning-curve effect and supporting hypothesis 1_1. Learning curves are often characterized in terms of a progress ratio, $p$. The progress ratio is calculated based on the estimated learning coefficient, $\beta_i$:

$$p = 2^{-\beta_i}.$$  

With that information, we can calculate how much productivity increases for each doubling of cumulative experience. Based on column 1 of Table 5, a progress ratio for organization learning was $p = 0.929$. That is, when the organization doubles problem-solving experience, the ART decreased approximately 7.1%. While there is considerable variance in progress ratios found in previous studies, the modal progress ratio for manufacturing firms is approximately 80% (Dutton and Thomas 1984), which means a 20% productivity enhancement results from the doubling of cumulative experience. Thus, the computing call center demonstrated a slower learning progress than manufacturing firms, which supports Hypothesis 1_2.

<Insert Table 5 about here>

In model 2, which examines learning effects by groups, the result still indicates a significant learning-curve effect (-0.127, p<0.001). The group dummy variables are significant, showing that the hours required to solve the first request are different by groups. In model 3, all three interaction terms are significant and negative, indicating significant learning curves in all three groups. Using a $t$-statistic, we found that the learning rate for the PG is much faster than those for the FG and the FS. This result shows that groups working with requests requiring surface-level application knowledge learned at a significantly faster rate, on average, than did the group that work on in-depth fundamental technical knowledge: PG-FG: $t=-3.575$ (p<0.001) and PG-FS: $t=-4.273$ (p<0.001). The $t$-statistics of PG-FS ($t=-0.938$) do not
indicate a significant difference between the learning rates for the FG and the FS. This finding partially supports Hypothesis 2.

In addition to estimation based on the learning equation, we analyzed the change of ART with a duration model (Kiefer 1988). Our study is more concerned with learning progress rather than the shape of survival or hazard function of resolution time in a computing call center. The notion of the change in the hazard rate induced from cumulative experience is comparable to the learning-curve effect. In many studies, the hazard function itself is more interesting than the survival function. Table 6 summaries the results of survivor analysis, where results based on two distributional assumptions of resolution time are shown: Exponential and Weibull distribution. The results from both distributions seem to be somewhat similar, but we found that the shape parameter $p$ of Weibull regression is significantly greater than 1 ($p = 3.290$). Given that (1) $p$ value of 1 corresponds to an exponential model: the constant hazard rate over time, (2) $p > 1$ indicates that the hazard rate increases with time, and (3) $p < 1$ indicates that the hazard rate decreases, we have strong evidence to reject a constant hazard rate model (exponential model). Thus, we test the relevant hypotheses based on the Weibull distribution. The estimated hazard rate of 1.372 differs significantly from 1 ($p = 0.000$). A hazard rate greater than one indicates the positive (increasing) impact of the covariate on the hazard rate and so we can conclude that the cumulated problem-solving experience is more likely to help solve the next problem over a short period of time, supporting Hypothesis 1 as well. Also, the comparison of hazard ratios among consultant groups is consistent with the results from the learning equation, supporting Hypothesis 2.

Variance of resolution times significantly decreases as the organization accumulates experience (-0.066, $p<0.001$), supporting Hypothesis 1. Furthermore, we checked the change of variance of resolution times by groups (see the Table 7). We found that the performance progress in terms of stable problem-solving procedure is significant only in the generalist groups (PG and FG).

<Insert Table 7 about here>

Analyzing knowledge transfer with model(s) 5 and 6, we were concerned about multicollinearity because all interaction terms and total cumulative requests vary in the same direction (i.e., all explanatory
variables except the dummy variables increase, as time goes on.) The change of the magnitude and significance of $\beta_{1h}$’s from model 5 to model 6 is a practical evidence of multicollinearity (refer to Table 8). And we checked VIF (Variance Inflation Factors) and found that in Model 6 the average VIF of 64.44 is higher than 10, indicating severe multicollinearity\(^9\). But, we can see strong evidence supporting Hypothesis 3 with the significant coefficient of total cumulative requests ($\beta_2 = -0.256$, p<0.001) with the small VIF of $GQ_0$ (3.06). That is, the cumulative experience in problem types other than a specific problem type leads to performance improvement in the specific problem type. Additionally, we empirically ascertained that knowledge transfers across IT problem types occur, through analysis based on a duration model.

<Insert Table 8 about here>

### 7. Discussion and Conclusion

This research makes several contributions. It is the first empirical investigation of the learning effect in IT knowledge workers, which turns out to be slower than other industries by around 65% (=1-7.1/20). By examining the basic nature of IT knowledge, we introduce two concrete concepts – new knowledge classification matched to IT consultants’ job assignment and IT problem types –, and measure their effect on the learning curve of IT knowledge workers.

Our analysis shows that the FS group employing a specialization strategy has a flatter learning curve than generalist groups engaged in a diversification strategy. Although the result could be interpreted as indicating that specialization strategies are not desirable in a computing call center, we do not advocate this interpretation. Previous studies on learning indicates a number of implicit and explicit references as to how learning might be positively affected by task specialization (Fisher and Ittner 1999; Flueckiger 1976; Schilling et al. 2003; Von Hippel 1998). This specialization allows individuals or organizations to focus all of their time and energy toward one task and to complete the most repetitions of a particular kind of problem within a finite time period. We believe that the nature of the task explains the difference in the

\(^9\) VIF is calculated based on OLS estimation.
learning rates rather than whether specialization is adopted. Our findings indicate that the generalist group working on requests requiring surface-level application knowledge learned at a faster rate than did the specialist group solving problems involving in-depth technical knowledge. Although the learning rate of the FG group is not significantly different from the learning rate of the FS group, the learning coefficient of the FG group is greater than that of the FS group (-0.110 vs. -0.071). Model 4 also reveals that the performance improvement in terms of the stability of problem-solving is significant in only the generalist groups (PG and FG). The coefficient is insignificant in the FS group – but, the direction is consistent with our expectation. In summary, both ART and VAR are reduced at a faster rate for generalists than for specialists. That is, the learning rate of application-level knowledge is significantly faster than that of technical-level knowledge in both performance measures (refer to Figure 4).

In addition to contributing to a theoretically grounded study of learning in an IT technical service environment, our study has several implications for managerial practice. First, among these is the implication for staffing in service organizations. Gans and Zhou (2002) showed that a myopic staffing policy could be optimal, where a myopic policy means the optimization of a one-period static problem for each period rather than the dynamic multi-period problem. A key assumption underlying their analysis is that no learning occurs in the IT service provider environment. Although our estimated learning progress in IT knowledge workers is slower than what is typically found in manufacturing, it is significant. This suggests that it would be productive to incorporate learning progress into staffing models. The finding of learning progress and of different learning rates by groups keeps open the possibility of the superiority of a dynamic staffing strategy.

Our results also offer insight into whether IT consultants should specialize in particular problem types. In the generalist group, cumulative experience is measured without discrimination of problem types, and learning-by-doing experience means IT knowledge accumulation in all problem types. There are two possible explanations for the significant learning effect shown in the generalist group: (1) knowledge accumulation in one problem type may induce performance improvement in another problem type.
(knowledge transfer occurs), and (2) knowledge accumulation in a particular problem type induces the performance improvement in only the corresponding problem type (knowledge transfer does not occur).

The result of model 6 strongly supports the first explanation—that is, the productivity of problem-solving is enhanced not only from experience in a particular problem type but also from the experience gained in other problem types. Therefore, we can say that “specialization” strategy does not have to be adopted in the generalist group because members benefit from solving different types of problems (related variation effect).

Even though it is not hypothesized, we find that the classification of IT problem types moderates the learning relationship as shown in the second column of Table 8 (i.e., the learning rate of IT knowledge workers varies depending on IT problem types.) One potential explanation of this finding is the difference in the characteristics of each knowledge pool (i.e., the difference in knowledge evolution speed or the size of the whole knowledge pool may cause the different learning rates according to IT problem types.) Therefore, we believe that true effectiveness of learning mainly depends on the portion of newly acquired knowledge over the whole knowledge pool rather than simple knowledge increments from unit to unit. The knowledge pool may be so big or abstract that one requires a prohibitively lengthy experience to benefit from learning effect, showing relatively slow (or no) learning progress. For example, consultants do not show learning effect in network problems, which include more diverse areas (dialup, DSL, Ethernet, registration, wireless, IP extension, Routing, and VPN) than the four other problem types.

7.1. Robustness

The starting point of our data is the time when the center started using a “new” call tracking system or knowledge management system. The introduction of the Remedy system might have reset the process of knowledge accumulation in the organization, but previous experience embedded in the organization could influence the learning progress during our research period. Unfortunately, we cannot measure unknown history of previous experience. FGs and FSs are full-time staff members, and the majority of the consultants in both groups have had careers in relevant areas ranging from 7 to 20 years.
However, we could not individually examine their career trajectory, due to the inability to obtain what the center considered private information. Given this constraint, the previous experience of individual consultants before joining the center could not be controlled in our setting. To check the robustness of the estimation shown above, we tried to control for the impact of unknown experience with the method used by Darr et al. (1995). We added the parameter for capturing prior unknown experience (z) into the conventional learning equation and ended up with the following equation;

\[ \ln(RT_{jt} / q_{jt}) = \beta_0 + \beta_1 \ln(Q_{jt-1} + z) + u_{jt}. \]

This is a non-linear equation and so we estimated all the parameters with non-linear least square estimation. We found that z does not make any significant change to other coefficients.\(^{10}\) Thus, even when unknown previous experience is taken into account, it shows that our results regarding learning progress is valid.

We examined the influence of various factors suggested by the literature and the research site as control variables: (1) the number of consultants, (2) the criticality level of requests, (3) the volume of requests in a unit of time, (4) the ratio of requests over the number of consultants – the economy of scale –, and (5) personnel movement in or out of the center. We found that these variables did not influence the learning curve (see the online appendix for control variables.) Additionally, we tried to add calendar time to investigate the influence of technical change associated with the time flow. There is a significant correlation (0.98) between the experience variable and calendar time, regardless of the unit of time (weekly, quarterly) and so we cannot analyze these two factors simultaneously in a regression model. We believe that three characteristics of our site contribute to the high correlation. First, there was continuous operation during the period (i.e., neither breakdowns nor interruption of operation). Second, in contrast to the environments of other studies such as pizza franchises (Darr et al. 1995) or aircraft producers (Benkard 2001), the operation in the center does not have a viable substitute and is not affected by economic conditions such as the appearance of a competitor. Third, a linear increment in experience in the long-term perspective (shown in the correlation coefficient of 0.98) is observed even when there is

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\(^{10}\) When we estimated the equation, the estimate of the unknown history (z) was negative in the FG group, and it was an unrealistically huge value in the FS group and the organization. So, we did exponential or log transformation (exp(z) or ln(z)).
fluctuation in the short-term due to seasonality. Given that, we examined two potential contributors to performance variation, which were expected to be captured with calendar time. First, the center has used the same Remedy system over the study period. Neither operation nor technical change inside the center was observed. But, technical change occurring outside the center, such as the advancement of search engines (Google or Yahoo), may result in performance gains. Consultants told us that they were unlikely to get assistance from outside sources because they have a better knowledge resource (recall the archive in the Remedy system DB which we refer to as pseudo working group) and most questions (reported problems) are related to the unique environment at Carnegie Mellon University. Given that, we could conclude that the variations expected to be explained by a calendar time are not a likely alternative explanation for the increased productivity.

Although the results are consistent with our predictions, there may be alternative explanations for our findings. One explanation is selection bias: a consultant can select the requests he or she is more familiar with because consultants can see the subject/title fields of requests in the queue. That is, consultants could select easier requests to solve as they gained experience. According to this reasoning, selection rather than learning would drive the performance improvements we observe. This explanation, however, is not viable for two reasons. First, there is no incentive for consultants to distinguish requests. Consultants do not benefit by solving more requests or by solving them more quickly. Second, consultants can ask for assistance from other consultants or furthermore, transfer a request to upper-level supporters. Therefore, there is no reason they should be reluctant to pick up a request in the order they were received. Thus, selection bias is not a viable alternative explanation in the context.

7.2. Limitations and Future Research Direction

Our results do not enable us to determine how IT problems are related (symmetric or asymmetric), how much they are related to each other, and ultimately which dimensions of relatedness drive knowledge transfer across IT problem types. Even if we are very interested in one-to-one mutual influence among problem types, we cannot analyze and answer the empirical question due to the multicollinearity problem.
we described. Future research is required to show the IT knowledge schema in learning relationship across IT problem types.

Although our findings in the learning curve of IT knowledge workers in a computing call center are meaningful in theory and practice, the uniqueness of our data and the operational definition used in this study might prohibit the generalization of results. For example, a potential alternative explanation for why the learning progress for FG’s and FS’s is slower than that for PG might be the influence of the job career of FG’s and FS’s. That is, specialists might show a lower learning rate because they have been doing this job longer and have already reached the flatter part of their learning curves. Even though we confirmed that unknown experience did not affect our results, future research replicating our analysis in a different context is needed.

The unit of analysis is somewhat complex. Even if one consultant has the ownership of a request, problem-solving tasks are achieved in a group setting. Here, we assume that the individual consultant’s assistance to other consultants is proportional to the accumulated experience due to the lack of information of sub-groups that solved each problem. Previous research has indicated that a team’s performance can be affected by its development of transactive memory systems (or knowledge of who knows what) (Lewis et al. 2005; Liang et al. 1995; Moreland et al. 1998; Wegner 1986), which can influence the degree to which group members are dependent on each others’ knowledge. Future research should attempt to extend our findings by explicitly examining the effect of well-developed transactive memory or peer effect on performance in the IT technical service environment.

This study develops a new knowledge classification and demonstrates its moderating effect on learning rates. The classification is practically based on an observable job assignment. However, the concept will not be constant over time. The classification may need to be modified depending on the organization-specific or user-specific characteristics over time (e.g., as the general level of technical competency in a user community changes, it will have an effect on the job assignments of consultants).

In closing, our results indicate that organizational/group learning occurs, even in knowledge work in a computing call center characterized by high volatility. Further, knowledge transfer occurs across
problem types. Thus, organizational learning and knowledge transfer are significant sources of performance improvements in the call center. These organizations should be designed to facilitate learning, because such a focus has the potential to improve organizational productivity through dynamic optimal staffing decisions.

<table>
<thead>
<tr>
<th>Type</th>
<th>Sub-divided problems</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Virus</td>
</tr>
<tr>
<td>2</td>
<td>Network</td>
</tr>
<tr>
<td>3</td>
<td>OS</td>
</tr>
<tr>
<td>4</td>
<td>E-mail</td>
</tr>
<tr>
<td>5</td>
<td>Account</td>
</tr>
<tr>
<td>6</td>
<td>The Others</td>
</tr>
<tr>
<td></td>
<td>Vaccine like Norton Antivirus, report of viruses, the solution of viruses</td>
</tr>
<tr>
<td></td>
<td>Dialup, DSL, Ethernet, registration, wireless, IP extension, Routing, VPN</td>
</tr>
<tr>
<td></td>
<td>Configuration, Devices and Ports, Installation, Unix, MS window</td>
</tr>
<tr>
<td></td>
<td>Aliases, boards, delivery, Spam</td>
</tr>
<tr>
<td></td>
<td>Authentication, Andrew account, account service</td>
</tr>
<tr>
<td></td>
<td>Cluster, Testing, Unknown, Call center policy, Printing, Abuse(Break-in, Harassment, PW, policy)</td>
</tr>
</tbody>
</table>

Table 2.1. IT Problem type classification
<table>
<thead>
<tr>
<th>Variable</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>Individual consultant</td>
</tr>
<tr>
<td>$j$</td>
<td>Consultant group: 0=PG, 1=FS, 2=FG</td>
</tr>
<tr>
<td>PG</td>
<td>Part-time student generalist group</td>
</tr>
<tr>
<td>FG</td>
<td>Full-time staff generalist</td>
</tr>
<tr>
<td>FS</td>
<td>Full-time specialist</td>
</tr>
<tr>
<td>$t$</td>
<td>Calendar time in weeks (0,178)</td>
</tr>
<tr>
<td>$q_{jt}$</td>
<td>Number of requests solved by group $j$ in week $t$</td>
</tr>
<tr>
<td>$RT_{jt}$</td>
<td>Summation of resolution times, which group $j$ consumed to solve $q_{jt}$ requests in week $t$</td>
</tr>
<tr>
<td>$Var(RT_{jt})$</td>
<td>Variance of resolution times, which group $j$ consumed to solve $q_{jt}$ requests in week $t$</td>
</tr>
<tr>
<td>$Q_t = \sum_{x=0}^{t} \sum_{j=0}^{2} \sum_{i=1}^{n} q_{ijt}$</td>
<td>Cumulative number of all requests solved through week $t$ in the organization</td>
</tr>
<tr>
<td>$GQ_{jt} = \sum_{x=0}^{t} \sum_{i=1}^{n} q_{ijt}$</td>
<td>Cumulative number of requests solved by group $j$ through week $t$</td>
</tr>
<tr>
<td>$PT_p$</td>
<td>Dummy variable for problem type $p$. $p=0, 1, 2, ..., 5$</td>
</tr>
<tr>
<td>$PT_p - q_{jt}$</td>
<td>Number of problem type $p$-related requests solved by group $j$ in week $t$</td>
</tr>
<tr>
<td>$PT_p - Q_{jt} = \sum_{x=0}^{t} PT_p - q_{jt}$</td>
<td>Cumulative number of problem type $p$-related requests solved by group $j$ through week $t$</td>
</tr>
<tr>
<td>$PT_p - RT_{jt}$</td>
<td>Summation of resolution times, which group $j$ consumed to solve problem type $p$-related requests, $PT_p - q_{jt}$ in week $t$</td>
</tr>
</tbody>
</table>

Table 2.2. Variables and operational definition

<table>
<thead>
<tr>
<th>Email</th>
<th>Phone</th>
<th>Walk-in</th>
<th>Others (DSP, Voice mail, etc)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>120610 (69.2%)</td>
<td>37654 (21.6%)</td>
<td>14180 (8.1%)</td>
<td>1283 (0.9%)</td>
<td>174056</td>
</tr>
</tbody>
</table>

Table 2.3. The distribution of requests across contact ways

<table>
<thead>
<tr>
<th>Group</th>
<th>Virus</th>
<th>Network</th>
<th>OS</th>
<th>Email</th>
<th>Account</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG</td>
<td>Average</td>
<td>6.78</td>
<td>13.34</td>
<td>11.71</td>
<td>14.74</td>
<td>11.68</td>
</tr>
<tr>
<td></td>
<td>Variance of RT</td>
<td>218.79</td>
<td>533.04</td>
<td>430.57</td>
<td>671.44</td>
<td>521.25</td>
</tr>
<tr>
<td></td>
<td>#</td>
<td>3047</td>
<td>6562</td>
<td>1731</td>
<td>7257</td>
<td>3638</td>
</tr>
<tr>
<td>FG</td>
<td>Average</td>
<td>7.81</td>
<td>16.15</td>
<td>10.31</td>
<td>17.13</td>
<td>17.10</td>
</tr>
<tr>
<td></td>
<td>Variance of RT</td>
<td>367.02</td>
<td>852.41</td>
<td>460.25</td>
<td>762.38</td>
<td>745.12</td>
</tr>
<tr>
<td></td>
<td>#</td>
<td>5608</td>
<td>5059</td>
<td>1736</td>
<td>9011</td>
<td>11014</td>
</tr>
<tr>
<td>FS</td>
<td>Average</td>
<td>31.84</td>
<td>20.37</td>
<td>32.59</td>
<td>37.58</td>
<td>30.21</td>
</tr>
<tr>
<td></td>
<td>Variance of RT</td>
<td>1214.73</td>
<td>2140.45</td>
<td>989.25</td>
<td>1407.84</td>
<td>1746.78</td>
</tr>
<tr>
<td></td>
<td>#</td>
<td>1362</td>
<td>8130</td>
<td>663</td>
<td>1447</td>
<td>804</td>
</tr>
</tbody>
</table>

Table 2.4. Descriptive statistics
### Table 2.5. Learning Curve Estimates (ART) by groups

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative requests</td>
<td>-0.107***</td>
<td>-0.127***</td>
<td>-0.791^</td>
</tr>
<tr>
<td></td>
<td>(0.0149)</td>
<td>(0.017)</td>
<td>(0.447)</td>
</tr>
<tr>
<td>FG Dummy</td>
<td>0.563***</td>
<td>-0.791^</td>
<td>-0.748^</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.448)</td>
<td>(0.448)</td>
</tr>
<tr>
<td>Specialist Dummy</td>
<td>0.094***</td>
<td></td>
<td>-0.748^</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td></td>
<td>(0.448)</td>
</tr>
<tr>
<td>PG × Q_{t-1}</td>
<td>-0.252***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FG × Q_{t-1}</td>
<td>-0.110***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FS × Q_{t-1}</td>
<td>-0.071^</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>177</td>
<td>503</td>
<td>501</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-56.10</td>
<td>-340.47</td>
<td>-332.67</td>
</tr>
</tbody>
</table>

Standard errors are shown in parentheses
^ Significant at \( p < 0.10 \)  *Significant at \( p < 0.05 \)  **Significant at \( p < 0.01 \)  ***Significant at \( p < 0.001 \)

### Table 2.6. Hazard Ratio Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exponential</th>
<th>Weibull</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative requests</td>
<td>1.111^</td>
<td>1.372***</td>
</tr>
<tr>
<td></td>
<td>(0.713)</td>
<td>(0.108)</td>
</tr>
<tr>
<td>FG Dummy</td>
<td>3.976</td>
<td>108.963***</td>
</tr>
<tr>
<td></td>
<td>(3.948)</td>
<td>(120.025)</td>
</tr>
<tr>
<td>FS Dummy</td>
<td>3.556</td>
<td>70.311***</td>
</tr>
<tr>
<td></td>
<td>(3.689)</td>
<td>(84.892)</td>
</tr>
<tr>
<td>PG × ln(Q_{t-1})</td>
<td>1.341***</td>
<td>2.153***</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.219)</td>
</tr>
<tr>
<td>FG × ln(Q_{t-1})</td>
<td>1.107^</td>
<td>1.222***</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>FS × ln(Q_{t-1})</td>
<td>1.074</td>
<td>1.165^</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>P</td>
<td>3.290</td>
<td>2.209</td>
</tr>
<tr>
<td></td>
<td>(0.183)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>N</td>
<td>177</td>
<td>501</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-186.42</td>
<td>-553.81</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-60.19</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-356.2048</td>
</tr>
</tbody>
</table>

Standard errors are shown in parentheses
^ Significant at \( p < 0.10 \)  *Significant at \( p < 0.05 \)  **Significant at \( p < 0.01 \)  ***Significant at \( p < 0.001 \)
### Table 2.7. Learning Curve Estimates (VAR) by groups

<table>
<thead>
<tr>
<th>Variable</th>
<th>PG</th>
<th>FG</th>
<th>FS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative requests solved in each group j at week t-1</td>
<td>-0.417*</td>
<td>-0.071*</td>
<td>-0.046</td>
</tr>
<tr>
<td></td>
<td>(0.190)</td>
<td>(0.036)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-345.7763</td>
<td>-168.3380</td>
<td>-159.8686</td>
</tr>
</tbody>
</table>

Standard errors are shown in parentheses

*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$

### Table 2.8. Learning Curve Estimates (ART) by IT problem types

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulative requests at week t-1</td>
<td>2.120***</td>
<td>-0.256***</td>
</tr>
<tr>
<td></td>
<td>(0.689)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>Virus Dummy</td>
<td>1.731**</td>
<td>-0.406</td>
</tr>
<tr>
<td></td>
<td>(0.741)</td>
<td>(0.843)</td>
</tr>
<tr>
<td>Network Dummy</td>
<td>2.714***</td>
<td>1.236*</td>
</tr>
<tr>
<td></td>
<td>(0.597)</td>
<td>(0.680)</td>
</tr>
<tr>
<td>OS Dummy</td>
<td>2.061**</td>
<td>-0.141</td>
</tr>
<tr>
<td></td>
<td>(0.748)</td>
<td>(0.891)</td>
</tr>
<tr>
<td>Account Dummy</td>
<td>1.731**</td>
<td>0.164</td>
</tr>
<tr>
<td></td>
<td>(0.680)</td>
<td>(0.800)</td>
</tr>
<tr>
<td>Virus Dummy $\times PT_1 - Q_{0t}$</td>
<td>-0.306***</td>
<td>-0.035</td>
</tr>
<tr>
<td></td>
<td>(0.099)</td>
<td>(0.116)</td>
</tr>
<tr>
<td>Network Dummy $\times PT_2 - Q_{0t}$</td>
<td>-0.123</td>
<td>0.152</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>OS Dummy $\times PT_3 - Q_{0t}$</td>
<td>-0.373***</td>
<td>-0.137</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Email Dummy $\times PT_4 - Q_{0t}$</td>
<td>-0.156*</td>
<td>0.120</td>
</tr>
<tr>
<td></td>
<td>(0.092)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Account Dummy $\times PT_5 - Q_{0t}$</td>
<td>-0.166*</td>
<td>-0.095</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-1561.679</td>
<td>-1552.121</td>
</tr>
<tr>
<td>N</td>
<td>1037</td>
<td>1037</td>
</tr>
</tbody>
</table>

Standard errors are shown in parentheses

*Significant at $p < 0.10$  **Significant at $p < 0.05$  ***Significant at $p < 0.01$

In model 6, some coefficients of interaction terms are positive. Recall that “total cumulative requests” includes whole experience across all IT problem types. When we use “the cumulative experience in problem types other than a specific problem type” instead of “total cumulative requests”, the coefficient of interaction terms in every problem type would be the sum of coefficient of interaction term and $\beta_2$. Then, the influence of experience on each problem type is negative as expected.
Figure 2.1. Individual consultant’s (PG) solution searching procedure
Figure 2.2. Problem solving workflow based on the request ownership change

Generalist Group

Specialist Group

Request queue

Request ownership: PG

Request ownership: FG

Request ownership: FS
Figure 2.3. Group working environment

Figure 2.4. Learning progress by knowledge types

Application-level knowledge

Technical-level knowledge
Chapter 3: Empirical Analysis of Mobile Voice and SMS service: A Structural Model

Abstract

In addition to the wireless telephone boom, a similar exponential increasing trend in wireless data service – short messaging services (SMS) –, is visible as technology advances. Given these interesting communication trends, we develop a structural model to understand mobile users' behavior in the individual level consumption of voice and SMS services, allowing for cross-service dependency. The key issues are the own-price elasticities and the cross-price elasticities of these services. The cross-price elasticity is of significant importance because the marketing activities are critically influenced by whether the goods are substitutes or complements. The research context also poses interesting econometric challenges – one-way and ‘step’ nonlinear pricing, and discrete (bundle choice)/continuous (quantity choice) mixture modeling. Using a detailed individual level consumption data, we find that there is a substitution effect between two services. We also find that the own price elasticity for voice services is relatively small compared to that for fixed phone service. Younger users are far more inelastic than the older group in four kinds of elasticities (own- and cross vs. voice and SMS). This is somewhat counter intuitive and gives some unique insight in understanding mobile service.

Key words: Mobile Demand Structure, A Discrete/Continuous Choice Model, Structural Model, Wireless Communication
1. Introduction

In most countries throughout the world, mobile (cellular) telephones have grown to be a key part of the telecommunication network – mobile telephones already account for a substantial portion of all telephone connections (almost one-third based on reports of OECD, 2001). The growth of wireless telephony networks has also made significant growth in wireless data services, specifically, short messaging services (SMS), which has become very popular in European, African, and Eastern Asian countries, changing the way users communicate. A recent McKinsey study finds that mobile services have generated billions in consumer welfare. Despite tremendous growth in these mobile services, our understanding of how users consume these services is still limited. Our paper examines the relationship between the two mobile services and further estimate the demand structure of the mobile services, reflecting the interdependency (cross-effect).

This study has important implications for practitioners and academicians. The understanding of user response to a typical nonlinear pricing scheme set by telephone companies is important for managers because it allows them to optimally price their products. Also, if managers comprehend how SMS and voice interact (whether SMS is a substitute or complement to voice), they are able to predict direct and indirect impact of pricing and promoting and so make a better decision for business purposes. Wireless service providers have invested billions in data service and a prevalent belief in the industry is that the consumption of data service also increases the consumption of voice (NTT-DoCoMo). However, the mutual relationship has not been examined on an individual level in prior literature, presumably due to the lack of individual level data or relatively recent nature of this phenomenon. Andersson et al. (2006) analyzes the relationship of two services and the impact of network size on the relationships, but they still use a highly aggregated-level dataset, where the main dependent variable is “the total number of originated SMSs quarterly divided by the number of subscribers.” The analysis of the demand structure on an individual-level are expected to provide more insights and also requires a sophisticated analytical framework since the firms routinely offer two-part nonlinear tariffs and consumers encounter a discrete/continuous mixture choice problem for utility maximization. To our knowledge, this is the first
study that offers a methodology to estimate own- and cross-price elasticities for voice and SMS services based on individual level consumption data.

In more specific terms, this paper is composed of two parts. The first one is to develop a general model describing individual consumption behavior in two mobile services. Then, we explicitly allow for mutual dependence of two services and account for the endogeneity issue – e.g., the expected consumption bundle of two services (second choice) affect a plan choice (first choice). The framework incorporates four crucial elements that could affect users’ optimal consumption behavior: (1) substitutive or complementary relationship between two services, (2) price response parameters, (3) satiation points, and (4) inherent association between two satiation points (to be discussed in detail). These elements are embedded in the model as parameters to be estimated. The second part is to estimate the parameters. We derive the joint likelihood function, specifying an individual utility function.

The rest of the paper is organized as follows. We provide a background on the relevant literature in section 2. Our research context (data and pricing scheme) is provided and analyzed in section 3. We outline our analytic model in section 4 and estimation strategy in section 5. In the subsequent section, we discuss our results along with policy experiment. Finally, we conclude with a summary of our findings, limitation, and suggestions for future research.

2. Relevant literature

Telecommunication demand (modeling) literature has a rich history (see Taylor (1994)). Generally, telecommunication pricing and consumption behavior has been an intriguing research area because both mobile and fixed phone services have unique characteristics such as high fixed costs, almost zero marginal costs, and network externality, which pose interesting econometric challenges. More importantly, telecommunication traditionally has been a highly regulated industry and there has been lots of work on the impact of regulatory changes on user consumption behavior and social welfare.

One may classify research topics in telecommunication domain into three before SMS service was introduced: (1) evaluating the demand structure in fixed-line telecommunication, (2) examining the
impact of extra services such as extended area service (EAS), and (3) evaluating the mobile communication demand. In examining the demand structure of fixed phone service, many studies estimate the price elasticity of demand in various contexts. Taylor and Kridel (1990) makes distinction between access and usage of telephones and model them while calculating the price elasticity for telephone demand. Distinguishing the usage-based (metered) and flat-rate pricing, some researchers investigate how users choose one over the other and also how their demand changes when they choose flat-rate pricing as opposed to usage-based plans (Park et al. 1983). Kling and Ploeg (1990) calculates price elasticities given in unique contexts. Miravete (2002) models the user uncertainty of the number of minutes demanded in the next month when choosing a plan today. For the example of the second category, Kridel (1988) estimates the proportion of residential customers that would subscribe to EAS in situations where EAS was not previously available. Martins-Filho and Mayo (1993) studies the impact of EAS on both local and long distance demand and subsequently on social welfare. After wireless telephone service became widespread, the main research stream has been to examine (1) the demand elasticity of mobile subscription (or penetration) or price mark-ups and costs for cellular providers and (2) the degree of competition/substitution between mobile and fixed telephones in various situations such as “substitute for long distance fixed phone service” and (3) cross effect of fixed phone service and wireless service (Ahn and Lee 1999; Danaher et al. 2001; Garbacz and Thompson 2007; Gruber 2001; Hausman 1999; Miravete and Röller 2004; Rodini et al. 2003; Sung and Lee 2002). Recently, Economides et al. (2005) reports that telecommunication demand can be shifted as a function of cellular service used by the household as well. Given that SMS service is omnipresent, the interaction of voice and SMS services provides an interesting and attractive research avenue in the telecommunication area.

From the perspective of modeling, our research goal associated with the demand structure of two services is on the same line of one of the recently arising research streams (multiple category purchase behavior) in marketing discipline. Researchers have begun to understand cross-category relationships in consumers’ decision-making, using multi-category models (see Seetharaman et al. (2005) for a review of this topic). The recognition of cross-category dependencies implies that a consumer’s purchase decisions
across categories are not independent. In other words, the consumer’s decision of whether to buy in one category depends on the consumer’s corresponding decision in the related category and also the decision of how much to buy in one category depends on the consumer’s corresponding decision in the related category (Chiang 1991; Niraj et al. 2005; Seetharaman et al. 2005; Song and Chintagunta 2004). In the next section, we now provide some details on our data and outline key econometric challenges.

3. Research context

3.1. Data

We collected detailed consumption data of 6847 subscribers to a cellular service provider in Thailand – which is the 3rd largest firm having more than 2 million consumers – for 9 months beginning April 2002 through December 2002. The firm offers two kinds of communication services: wireless voice and SMS services.12 We have information regarding service consumptions on an individual level: (1) voice service usage measured in minutes for each month and (2) the number of SMSs exchanged for each month and (3) demographic information about the users (gender and age). Table 1 shows the pricing scheme offered – the pricing scheme did not change during our research period. Table 2 provides some descriptive statistics across age, gender and plan choice.

<table>
<thead>
<tr>
<th>Plan #</th>
<th>Fixed (entering) fee (baht)</th>
<th>Free minutes</th>
<th>Overtime charge of voice service (baht)</th>
<th>Charge of SMS service (baht)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>350</td>
<td>350</td>
<td></td>
<td>3/message</td>
</tr>
<tr>
<td>2</td>
<td>800</td>
<td>517</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1100</td>
<td>917</td>
<td>3/min</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1500</td>
<td>1217</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2000</td>
<td>2117</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1. Pricing Scheme (one-side and ‘step’ nonlinear pricing)

<table>
<thead>
<tr>
<th>Whole Sample</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voice</td>
<td>281.3</td>
<td>252.6</td>
<td>10.1</td>
<td>11845.3</td>
<td>59866</td>
</tr>
<tr>
<td>SMS</td>
<td>11.8</td>
<td>34.2</td>
<td>0</td>
<td>3106</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>G1: Age &lt;30</th>
<th>Voice</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Voice</td>
<td>329.8</td>
<td>299.5</td>
<td>10.2</td>
<td>11845.3</td>
<td>22483</td>
</tr>
</tbody>
</table>

12 The firm provided WAP service as well. WAP use typically means accessing email, stock quote or any other information on the cell phone. We have information on how many minutes of WAP service were used by each user in each month. But, the usage is too low to be able to analyze the effect.
<table>
<thead>
<tr>
<th></th>
<th>Voice</th>
<th>SMS</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>G2: 30&lt;=Age &lt;40</td>
<td>265.0965</td>
<td>223.455</td>
<td>10.08</td>
<td>6602.36</td>
</tr>
<tr>
<td></td>
<td>9.232893</td>
<td>33.69502</td>
<td>0</td>
<td>3106</td>
</tr>
<tr>
<td>G3: Age&gt;=40</td>
<td>203.6786</td>
<td>168.1059</td>
<td>10.05</td>
<td>2916.9</td>
</tr>
<tr>
<td></td>
<td>7.315656</td>
<td>26.84394</td>
<td>0</td>
<td>1079</td>
</tr>
<tr>
<td>S0: Female</td>
<td>287.1297</td>
<td>257.9581</td>
<td>10.08</td>
<td>11845.31</td>
</tr>
<tr>
<td></td>
<td>13.19011</td>
<td>31.63919</td>
<td>0</td>
<td>1558</td>
</tr>
<tr>
<td>S1: Male</td>
<td>274.3871</td>
<td>246.0002</td>
<td>10.05</td>
<td>6602.36</td>
</tr>
<tr>
<td></td>
<td>10.14611</td>
<td>37.10299</td>
<td>0</td>
<td>3106</td>
</tr>
<tr>
<td>Plan 1</td>
<td>248.9897</td>
<td>167.7135</td>
<td>10.05</td>
<td>2887.17</td>
</tr>
<tr>
<td></td>
<td>10.17615</td>
<td>31.56993</td>
<td>0</td>
<td>3106</td>
</tr>
<tr>
<td>Plan 2</td>
<td>642.5653</td>
<td>316.8856</td>
<td>19.62</td>
<td>4612.55</td>
</tr>
<tr>
<td></td>
<td>39.08512</td>
<td>59.03361</td>
<td>0</td>
<td>932</td>
</tr>
<tr>
<td>Plan 3</td>
<td>1011.397</td>
<td>505.8127</td>
<td>53.23</td>
<td>5169.68</td>
</tr>
<tr>
<td></td>
<td>44.27733</td>
<td>60.24948</td>
<td>0</td>
<td>633</td>
</tr>
<tr>
<td>Plan 4</td>
<td>1556.421</td>
<td>994.3582</td>
<td>168.72</td>
<td>11845.31</td>
</tr>
<tr>
<td></td>
<td>43.13287</td>
<td>54.75447</td>
<td>0</td>
<td>562</td>
</tr>
<tr>
<td>Plan 5</td>
<td>1994.418</td>
<td>889.3416</td>
<td>429.6</td>
<td>4334.71</td>
</tr>
<tr>
<td></td>
<td>27.53763</td>
<td>41.02427</td>
<td>0</td>
<td>188</td>
</tr>
</tbody>
</table>

Voice is measured with the amount of minutes consumed
SMS is measured with the number of messages

Table 3.2: Average usage statistics

3.2. One-side and “step” nonlinear pricing

As shown in Table 1, the research context shows a unique pricing scheme: (1) a two-part tariff in voice service (zero marginal cost before the fixed quota and positive marginal cost after the quota is exceeded), which is popular in mobile telecommunication, and (2) usage-based pricing in SMS with constant marginal cost.

First, this pricing is “one-side” nonlinear pricing because the pricing of only the voice service \( (q) \) is nonlinear – i.e., a quantity discount is available in only the voice service. The pricing of voice service is the second-degree price discrimination, where every consumer faces the same price schedule, but the schedule involves different (average) prices depending on the amounts of voice service consumed.
Second, the ratio of quantity discount is not linearly related to quantity. When consumers use the voice service under free minutes with a fixed fee paid, the (average) unit price depends on the plan chosen before consumers start using the service. This is the way non-linear pricing is realized by consumers. While the quantity of voice service is continuous, the quantity discount is not continuous but discrete. Here we will call it “step” nonlinear pricing. The one-side and step nonlinear pricing affects consumer utility maximization by generating the alternatives of unique budget constraints as shown in Figure 1.

![Figure 3.1. Illustration of budget constraints induced from diverse pricing schemes](image)

Because of the two-part tariff for voice services, the budget line is kinked. The budget constraint is an extension of kinked budget constraint analyzed by Moffitt (1990) because users can have different types of kinked budget constraints depending on a plan choice at the first stage (we will model the sequence of choices in the next section in detail). Under the same budget, every plan is characterized by distinctive areas indicating available amounts in voice and SMS dimensions and so the plan choice at the first stage can be modeled as a discrete bundle choice analyzed by Chung and Rao (2003). It should be noted that a plan choice shows the relationship between two services as well as relative preference to each service conditional on the budget. Figure 2 illustrates (1) feasible consumption bundles (areas) depending on a plan choice and (2) the mechanism of the optimal plan choice depending on the shape of utility functions in two dimensions. Suppose that a consumer has the amount of 2000 baht –entering fee for plan
5 – assigned to mobile communication. If the consumer selects plan 5 subject to the budget constraint, he/she cannot use any SMS service and instead use maximum 2117 minutes of voice service. The maximum of available minutes of voice service from plan 4 is around 1384 (1217+500/3). The comparison of plan 5 and plan 4 corresponds to the feasible area selection decision between “more than 1384 minutes of voice consumption and no SMS consumption” and “less than 1384 minutes of voice consumption and a maximum of 167 SMS service.” Consumers search for the optimal plan choice by iterating the comparison among 5 alternatives. Overlapping the available bundles and the shape of utility function, we can see the optimal voice plan choice vary according to the shape of utility function (actually the location of optimal bundle offering the highest utility). That is, there is no general dominant plan as shown in Figure 2. In the model, we assume that consumers have enough money to select any voice plan and a plan choice is contingent on the shape of the utility function – assuming that there is no substantial income effect, the utility function is quasi-linear in cost so that the equation does not depend on income. The assumption is supported by a relatively small portion of money assigned to telecommunication over a disposable income – average monthly bill amount to only 0.74% of the lowest income category (Economides et al. 2005).

![Figure 3.2. Feasible area conditional on a voice plan and optimal plan choice](image)

Figure 3.2. Feasible area conditional on a voice plan and optimal plan choice

\[13\] We will use the concept of satiation points to handle the issue in the next section.
4. Econometric Model

4.1. Conceptual background

4.1.1. Substitute/complement relationship

For the case of many goods, the change in the price of any goods induces income and substitution effects that may change the quantity of other goods demanded from the Slutsky equation. Then two goods are substitute if one goods may, as a result of changed conditions, replace the other in use. On the other hand, complements are goods that go together. That is, the substitute and complement relationships can be defined by referring to observed price reactions as $\frac{\partial X_i}{\partial P_j} > 0$ and $\frac{\partial X_i}{\partial P_j} < 0$. Reflecting on this notion in this study, we rely on the modified concept: $\frac{\partial X_i}{\partial X_j} > 0$ and $\frac{\partial X_i}{\partial X_j} < 0$, where $i$ and $j$ indicate voice and SMS service, respectively.

4.1.2. Separating cross effect, inherent association, and user heterogeneity

We need to exclude the noise affecting the cross-effect between two services. Manchanda et al. (1999) clarifies three reasons why multiple categories can be bought together on one shopping: (1) complementarity (or cross effect), (2) consumer heterogeneity, and (3) co-incidence. Since the main concern of this study is to examine cross effect, we need to control the two noises, namely (2) and (3). First, we need to account for user heterogeneity in the intrinsic preference for two mobile services, respectively. To control the inherent preference, we allow customer types to follow a probability distribution (to be discussed later) for stochastic specification. Furthermore, we also use a user demographic profile to account for the hypothesized heterogeneity conditional on them. The co-incidence is defined as all reasons except cross effect that could induce joint purchase (consumption) across categories (two services) – consumers may shop for many items on the same shopping trip because of habit or economic reasons such as spreading the cost of a trip over many items. In our context, while economic reason is not viable, habit can be a critical factor in over- or under-estimating the cross effect. As a result, it is crucial to distinguish the inherent association of two services and the cross effect. For
example, it is quite possible that heavy consumers of voice service are also likely to use SMS service much more regardless of the cross effect. The inherent association is formulated by allowing the correlation between consumer preferences (equivalently satiation points) for the services.

4.2. Analytical framework

Our analytical model is based on (discrete) plan choice and (continuous) consumed quantities across two services under the given one-side and “step” nonlinear pricing. Consumers are assumed to maximize utility by making two decisions at different points on the time horizon. A consumer makes a plan choice decision among discrete alternatives in the first stage. This choice is based on the expected optimal consumption bundle reflecting the cross effect. The consumer decides a vector with two continuous quantities of service usage in the second stage. As a result, the analytic framework takes the form of a (two stage) discrete/continuous mixture choice model.

Hanemann (1984) developed a unified framework for formulating econometric models of discrete/continuous choices in which both discrete and continuous choices aim at the same underlying utility maximization decision. But, in the model, the alternatives for discrete choices are essentially (perfect or near perfect) substitutes and thus a consumer prefers to buy only one option (e.g., A brand) at any time and the continuous choice is the magnitude of the option chosen. Then, discrete choice is related to one (A brand) among diverse alternatives (one category including A, B, and C) so that the choice shows the preference of A – actually, the attributes involved in A – over the others. An important early papers that lay the blueprint for these modeling contexts estimate their models with binary discrete choice models such as logit and probit (Albert and Chib 1993) or the multinomial brand choice context (Rossi et al. 1996). Approach used in these studies, however, is not fit in our context for several reasons. First, because the majority of consumers select both services simultaneously, the assumption that only one alternative has to be selected on a discrete choice occasion is not appropriate. In addition, the continuous quantity decision in the second stage may not be addressed well by the (nested) logit model, even though we can transform continuous variables into discrete variable as done by Niraj et al. (2005), which will
cause loss of information. Second, in the context, the discrete choice is a bundle choice of a combination of two service consumptions as explained above. Therefore, choice parameters – the operationalization of specific attributes of the bundle (or equivalently plan choice) – such as average free minutes allowed in plan choice, cannot represent clearly the cross effect of our main concern. In a mixed discrete/continuous context, the modeling separately of the two decisions – using a logit model for the discrete choice and regression models for the continuous decision – should be incorrect due to endogeneity problem if the quantity decision is not statistically independent of the choice decision and vice versa. The bias occurs because the regression models omit a relevant variable and the inefficiency in the logit model arises because the information contained in the data on the continuous outcomes is ignored (Krishnamurthi and Raj 1988). Therefore, Krishnamurthi and Raj (1988) first estimates the choice parameter with a discrete choice model and then estimates the regression model based on the parameters estimated after correcting selectivity bias. In a similar line, the two-step approach has been applied to estimate the mixed discrete and continuous model on multiple category purchase (Chiang 1991; Chintagunta 1993; Lee and Trost 1978). The simultaneous equation approach proposed by many studies is not applicable because there is no price variation in our dataset. Another approach is to treat different combinations (three element vector of discrete plan choice and two continuous consumptions) as different multinomial choice alternatives. However, this approach is not viable because of immense alternatives caused by the big variation in consumption.

In our context, it is obvious that two decisions are statistically dependent. This violates the basic assumption of the two-step approach (limited information MLE). So we have to estimate the model with full information MLE. Here, we attempt to derive the joint likelihood function for the observed consumption data from general distributional assumptions regarding individual heterogeneity and random error terms.

4.3. User utility specification

We consider individuals indexed by $i=1,2,\ldots,N$. The individuals choose voice plans from the set
of available plans, indexed by \( k = 1, 2, \ldots, 5 \) and then choose continuous quantities \((q_{ik}, s_{ik})\), conditional on the plan choice. When a user selects plan \( k \), the user must pay a fixed fee \( T_k \) to sign up for the plan \( k \), and is allowed to use free minutes of voice service \( FQ_k \). Once the user exceeds the given free minutes, she/he has to incur the marginal cost, \( p_q \) per unit. Thus, each plan can be characterized by \( T_k \) and \( FQ_k \). We assume that consumers spend the remainder of their income on an outside good, \( y_i \) at price 1.\(^{14}\)

We assume that the utility an individual \( i \) obtains from consumption of two services on plan \( k \), at the month \( t \), is quadratic.

\[
U_{it}(q_{ik}, s_{ik}, y_i | \theta_{iq}, \theta_{is}, b_q, b_s, b_{int}) = \frac{1}{b_q} \left( \theta_{iq} q_{ik} - \frac{q_{ik}^2}{2} \right) + \frac{1}{b_s} \left( \theta_{is} s_{ik} - \frac{s_{ik}^2}{2} \right) + b_{int} q_{ik} s_{ik} + y_i \tag{1}
\]

Here, \( b_q \) and \( b_s \) represent price response parameters, respectively, which will be used for calculating own- and cross-price elasticity. The point, \((\theta_{iq}, \theta_{is})\) represents a user’s type and it varies across users depending on the individual’s inherent preferences of the two services. Bigger \((\theta_{iq}, \theta_{is})\) represents higher preference in the service. \((\theta_{iq}, \theta_{is})\) is closely related to the concept of consumer satiation points – a satiation point is the maximum level of consumption desired for these services and so a consumer would not demand more than the satiation point even if the price were zero.\(^{15}\) Such a quadratic utility structure reflecting the concept of satiation is frequently modeled in telecommunication demand literature (e.g., Economides et al. 2005; Miravette et al 2004). In equation (1), the first term represents the utility obtained from the voice consumption, the second term the utility obtained from SMS service, and the fourth term utility obtained from the outside good.

As is commonly done, we assume that the utility from outside goods and the utility from the mobile service are separable – the consumption in mobile services does not affect the marginal utility obtained from outside good and vice-versa –\(^{16}\), whereas the utility obtained from voice service and the

\(^{14}\) The price of the outside good is normalized to one.

\(^{15}\) If there is no cross effect, \((\theta_{iq}, \theta_{is})\) is a satiation point.

\(^{16}\) Some utility from outside goods (e.g., fixed phone service and broadband services) might be dependent on that from wireless services. But, one justifies the assumption based on (1) the portion of utility from fixed phone service and broadband services is
one from SMS service are inseparable because the increment of consumption in one service can influence the consumer surplus by being weighted by both the consumption of the other service and \( b_{int} \) (cross effect parameter) – this mechanism is modeled through the third term in the equation (1) – in addition to the first (or second) term. That is, this implies that the demands for voice and SMS are dependent on one another.

Equation (1) is built on an assumption that cross effect is symmetric\(^\text{17}\) and also on the homothetic utility structure. Given the utility function, the utility from each service usage corresponds to the diminishing marginal utility and the negative impact of difference between satiation point and real consumption point on consumer surplus depends on only the absolute value of the gap.

Consumers first choose an optimal plan and then consume voice and SMS sequentially. We solve the problem with backward induction, starting from the second stage, where an individual subscriber selects the optimal quantities for voice and SMS, conditional on the choice of a plan \( k \) in the first stage, subject to the budget constraint (\( I_i \) indicates consumer \( i \)'s budget):

\[
I_i \geq T_k + p_q (q_{ikt} - FQ_k)^+ + p_s s_{ikt} + y_i
\]

where \( (q_{ikt} - FQ_k)^+ = \begin{cases} q_{ikt} - FQ_k & \text{if } q_{ikt} > FQ_k \\ 0 & \text{if } q_{ikt} \leq FQ_k \end{cases} \)

Substituting the budget constraint into the above objective function (indirect utility function) yields:

\[
\text{Max } U^*_{ikt}(q_{ikt}, s_{ikt} | k) \quad \text{subject to } I_i - T_k - p_q (q_{ikt} - FQ_k)^+ - p_s s_{ikt} 
\]

and

\[
= \frac{1}{b_q} \left( \theta_q q_{ikt} - \frac{q_{ikt}^2}{2} \right) + \frac{1}{b_s} \left( \theta_s s_{ikt} - \frac{s_{ikt}^2}{2} \right) + b_{int} q_{ikt} s_{ikt} + I_i - T_k - p_q (q_{ikt} - FQ_k)^+ - p_s s_{ikt}
\]

The first order condition is:

\[ \text{very small (or negligible) as compared to the utility from all other human activity and (2) there are no reports of a consistent relationship between them.}\]

\(^\text{17}\) Given our utility function, this symmetry can be shown by Young’s theorem: \( \partial U / \partial q_{ikt} \partial s_{ikt} \) is constant as \( b_{int} \).
\[
\begin{align*}
\frac{\partial U^*}{\partial q_{ik}} &= \frac{\theta_{iq} - q_{ik}}{b_q} + b_{int} s_{ik} - p_q = 0 \quad \text{if } q_{ik} > FQ_k \\
\frac{\partial U^*}{\partial q_{ik}} &= \frac{\theta_{iq} - q_{ik}}{b_q} + b_{int} s_{ik} = 0 \quad \text{if } q_{ik} \leq FQ_k \\
\frac{\partial U^*}{\partial s_{ik}} &= \frac{\theta_{is} - s_{ik}}{b_s} + b_{int} q_{ik} - p_s = 0
\end{align*}
\]

The comparison of the consumption bundles leading the highest utility from equation 4 – \((q_{ik}, s_{ik})^*\) – between when there is no cross effect of two services \((b_{int} = 0)\) and when there is cross effect \((b_{int} \neq 0)\), enables us to see the impact of the interaction term capturing the cross effect.\(^{18}\)

\[
(q_{ik}, s_{ik})^*_{b_{int}=0} = \begin{cases} 
(\theta_{iq} - b_q p_q, \; \theta_{is} - b_s p_s) & \text{if } q_{ik} > FQ_k \\
(\theta_{iq}, \; \theta_{is} - b_s p_s) & \text{if } q_{ik} \leq FQ_k 
\end{cases} (5-1)
\]

\[
(q_{ik}, s_{ik})^*_{b_{int} \neq 0} = \begin{cases} 
(\theta_{iq} - b_q p_q + b_{int} s_{ik}, \; \theta_{is} - b_s p_s + b_{int} q_{ik}) & \text{if } q_{ik} > FQ_k \\
(\theta_{iq} + b_{int} s_{ik}, \; \theta_{is} - b_s p_s + b_{int} q_{ik}) & \text{if } q_{ik} \leq FQ_k 
\end{cases} (5-2)
\]

There are four possible scenarios regarding the change of the optimal consumption bundle in two dimensions (see Table 3) We can intuitively divide it into two groups – symmetric of scenario (1) and (3) vs. asymmetric of scenario (2) and (4) –. Given the definition and utility specification, the cross effect must be symmetric, whatever its direction is: increasing in scenario (1) or decreasing in scenario 2. Because \(b_q, b_s, q_{ik}\), and \(s_{ik}\) are positive, the direction of the change depends on only the sign of \(b_{int}\) (positive or negative). The sign of \(b_{int}\) allows us to identify whether the cross effect is complementary or substitutive between two services.\(^{19}\) In scenario (1), \((b_{int} > 0)\), the consumption in one service induces more consumption in other service. As a result, positive \(b_{int}\) will be the evidence that one service plays a role of complementing the other service. Given the complement relationship, individuals can fulfill the utility maximization with the consumption of more than \((q_{ik}, s_{ik})^*_{b_{int}=0}\). In scenario (3), \((b_{int} < 0)\), voice service is a substitute of SMS service and vice versa. In the case of substitute-effect, the satiation point in

\(^{18}\) Because the consumption bundle giving maximum utility can or cannot be reached depending on individual heterogeneous satiation points and the given price scheme, we cease to call it optimal consumption. We will derive “real” optimal consumption bundle from the demand function in the next section. Here, all consumptions must be positive.

\(^{19}\) We can analyze the cross effect (or the influence of \(b_{int}\)) with the composition of satiation point (equivalently, consumer’s type).
one service can be partly fulfilled with the other service to the extent of the amount adjusted with $b_{int}$.

4.4. Demand function

We can derive two kinds of demand functions in subscribers selecting plan $k$: demand function 1 (DF1) and demand function 2 (DF2) in equation 6, by simultaneously solving the above first order conditions. But, there are practically three kinds of demand functions due to the two part tariff pricing scheme applied to only the voice service. The three different functions are split by indifference curves, \( (FQC_k, GEC_k, \text{ and } IDC_{min, k}), \) which are derived from comparison of generated utilities based on the indirect utility function, $U^* \bullet$– we can derive an indirect utility function, plugging \((q_{ikt}', s_{ikt}')\) from equation (6) into the utility function in equation (3).

(1) Demand Function 1, (DF1),

The customers with a relatively lower value composition: \((\theta_{iq}, \theta_{is}) = <IDC_{min, k}, FQC_k>\), can reach their optimal consumption level without incurring additional cost in voice service.

---

20 In terms of the implication of the coefficients, $b_{int}$ is comparable to $\gamma_{11}$ (cross effect) at the Bivariate Probit model of Manchanda et al. (1999), where $\gamma_{11} > 0$ if the two product categories are complements, and $\gamma_{11} < 0$ if they are substitutes.

21 They are all indifference curves in a user group selecting a certain plan and the abbreviations of Free Quote Curve, Great Eater Curve, and InDifference Curve.

22 This notation indicates that the point is between two curves (lines).
(2) Demand Function 1 (DF2)

Demand function 2 and 3 represent users’ consumption behavior when the voice consumption giving maximum utility is higher than the free minutes under a selected plan: $q_{ik}^* > FQ_k$ (or equivalently $(\theta_{aq}, \theta_{as}) = <FQC_k, IDC_{min,k+1}>$). The users located at the area keep consuming up to the free minute. When they reach a kinked point of budget constraint (or consume given free minutes), they will compare the marginal utility from one more minute of voice service and the marginal cost. When the marginal utility is lower than the marginal cost, they stop the consumption of voice service without incurring extra cost in voice service. This users’ consumption behavior corresponds to the demand function 2. As a result, their optimal consumption is less than the ideal optimal consumption ($q_{ik}^* = FQ_k$) in voice service. The user type showing this behavior falls in $<FQC_k, GEC_k>$. 

(3) Demand Function 3 (DF3)

If $(\theta_{aq}, \theta_{as}) = <GEC_k, IDC_{min,k+1}>$, the user consumes optimally by incurring marginal cost because the marginal utility at the free minute is greater than marginal cost. Ultimately, the user keeps consuming more voice service until the marginal utility is the same as the marginal costs.

It should be noted that optimal consumptions in the two services are determined simultaneously and that in both DF2 and DF3, the optimal consumptions in both services would be a less than ideal optimal consumption (satiation point) because the satiation point does not reflects marginal cost and thus the marginal cost prohibits users from consuming up to a satiation point.

We have to divide all users belonging to $< IDC_{min,k}, IDC_{min,k+1}>$, which indicates the specific area in two dimensions of $(\theta_{aq}, \theta_{as})$, into three sub-groups – the users in each group have the same demand function. We will derive indifference curves, ($FQC_k$, $GEC_k$ and $IDC_{min,k}$), in the next section.
if \( IDC_{\min,k} \leq (\theta_{iq}, \theta_{is}) < FQC_k \)
\[
\begin{align*}
q_{ik} &= \frac{\theta_{iq} + b_{m} b_{q} \theta_{is} - b_{m} b_{q} b_{s} p_{s}}{1 - b_{m}^{2} b_{q} b_{s}} \quad \text{DF(1)}
\end{align*}
\]
\[
\begin{align*}
s_{ik} &= \frac{\theta_{is} + b_{m} b_{q} \theta_{iq} - b_{s} p_{s}}{1 - b_{m}^{2} b_{q} b_{s}}
\end{align*}
\]
\[
\begin{align*}
\text{if} \quad FQC_k \leq (\theta_{iq}, \theta_{is}) < GEC_k
\end{align*}
\]
\[
\begin{align*}
q_{ik} &= FQ_k
\end{align*}
\]
\[
\begin{align*}
s_{ik} &= \theta_{is} + b_{m} b_{q} FQ_k - b_{s} p_{s} \quad \text{DF(2)}
\end{align*}
\]
\[
\begin{align*}
\text{if} \quad GEC_k \leq (\theta_{iq}, \theta_{is}) < IDC_{\min,k+1}
\end{align*}
\]
\[
\begin{align*}
q_{ik} &= \frac{\theta_{iq} + b_{m} b_{q} \theta_{is} - b_{m} b_{q} b_{s} p_{s} - b_{q} p_{q}}{1 - b_{m}^{2} b_{q} b_{s}} \quad \text{DF(3)}
\end{align*}
\]
\[
\begin{align*}
s_{ik} &= \frac{\theta_{is} + b_{m} b_{q} \theta_{iq} - b_{m} b_{q} b_{s} p_{q} - b_{s} p_{s}}{1 - b_{m}^{2} b_{q} b_{s}}
\end{align*}
\]
, where

\( IDC_{\min,k} = \{ (\theta_{iq}, \theta_{is}) \mid U^{*}(DF(3) \mid k - 1) = U^{*}(DF(1) \mid k) \} \)

\( FQC_k = \{ (\theta_{iq}, \theta_{is}) \mid U^{*}(DF(1) \mid k) = U^{*}(DF(2) \mid k) \} \)

\( GEC_k = \{ (\theta_{iq}, \theta_{is}) \mid U^{*}(DF(2) \mid k) = U^{*}(DF(3) \mid k) \} \)

4.5. User heterogeneity and indifference curves

We showed that each individual's demand function is determined by the user type, \((\theta_{iq}, \theta_{is})\). All users whose \((\theta_{iq}, \theta_{is})\) belongs to \(< IDC_{\min,k}, IDC_{\min,k+1} >\) select plan \( k \) as the best choice for utility maximization. As the first step (deriving \( IDC_{\min,k} \)), we classify users into 5 groups, which is equivalent to the number of plan choice. This enables us to characterize user heterogeneity from information of plan choice based on the next axioms:

1. If a user is indifferent between two plans (plan \( k \) and plan \( k+1 \)), the cost from plan \( k \) (the fixed fee of plan \( k \) and the variable cost depending on additional usage beyond the free minutes) and the cost from plan \( k+1 \) (only the fixed fee of plan \( k+1 \)) have to be identical, at the expected optimal consumption point in voice service.\(^{23}\) As a result, the consumer will choose a higher plan in order to realize the benefit of the nonlinear pricing scheme, as the value of \( \theta_{iq} \) exceeds a specific threshold, which is the function of three components:

\(^{23}\)Since the actual consumption is to some extent out of the consumer's control (in terms of bounded rationality), the expected optimal consumption is determined under uncertainty. But the uncertainty will not change our model once the impact of the uncertainty is zero mean.
(1) \((\theta_{iq}, \theta_{is})\), (2) plan characteristics \((T_k, FQ_k, p_q, \text{and } p_s)\), and (3) parameters to be estimated, \((b_q, b_s, \text{and } b_{\text{int}})\). Therefore, the ranking of the plans is monotone in \(\theta_{iq}\).

2. Even if the marginal cost of SMS service \((p_s)\) is identical regardless of plan choice, the plan choice is affected by \(\theta_{is}\) due to the role of either substitute or complement. However, the expected optimal consumption point in SMS is the monotone transformation of \(\theta_{iq}\), which is monotone in plan choice. Therefore, the ranking of the plans is monotone in \(\theta_{is}\) as well.

3. From axiom 2 and 3, a plan choice is ordered with the magnitude of \(\theta_{iq}\) (or \(\theta_{is}\)), despite of one side nonlinear pricing. That is, the next equation always holds:

\[
D_k = \{(\theta_{iq}, \theta_{is}) | U_{ik} \geq U_{ij}, \forall j \neq k \} = \{(\theta_{iq}, \theta_{is}) | U_{ik} \geq U_{ik+1} \& U_{ik} \geq U_{ik-1} | k \geq 2, \text{ } U_{ik} \geq U_{ik+1} | k = 1 \}
\]

, where \(D_k\) indicates \(<IDC_{\text{min},k}, IDC_{\text{min},k+1}>\).

4. The indifferent curve between plan \(k\) and plan \(k+1\) can be acquired by comparing consumer surplus generated from two plans. \(IDC_{\text{min},k} = \{(\theta_{iq}, \theta_{is} | k) | U^*(DF(3) | k - 1) = U^*(DF(1) | k)\}.

5. The shape of indifference curves (here, the slope of indifference lines) is identical across plans under the assumption that utility function is homothetic.

6. Because the indifference curves according to plan choice do not overlap one another, indifference lines from formula in Axiom 5 will be boundaries for clearly dividing five groups.

Comparing the indirect utility functions across five plans, we can acquire indifference curves which separate two adjoining plans (From Axiom 4). The indifference curves are given by:

\[
\theta_{is} = \frac{(2FQ_k p_q - 2b_{int}^2 b_q FQ_k p_q + b_q p_q^2 + 2b_{int} b_q p_q p_s - 2T_k + 2p_q^2 b_q b_s T_k + 2T_{k+1} - 2b_{int}^2 b_q b_s T_{k+1})}{2b_{int} b_q} \cdot \frac{\theta_{iq}}{b_{int} b_q} \tag{7}
\]

We can see that the indifference curve is affected by three sources: (1) \((\theta_{iq}, \theta_{is})\), (2) \((T_k, FQ_k, p_q, \text{and } p_s)\), and (3) \((b_q, b_s, \text{and } b_{\text{int}})\). As Axiom 5 says, all indifference curves have the same slope, \(-1/(b_q b_{\text{int}})\). The interpretation of the slope is identical to the interpretation of \(b_{\text{int}}\) – the positive value of \(b_{\text{int}}\) indicates a substitute or otherwise a complement (refer to the Figure 4) –. For a numerical example, plugging real value from our data in equation (7), the indifference curve of plan 1 and plan 2, \(IDC_{\text{min},2}\), is:

\[
IDC_{\text{min},2} \Rightarrow \theta_{is} = \frac{1000 + 3b_q + 6b_{int} b_q b_s - 1000 b_{int}^2 b_q b_s}{2b_{int} b_q} \cdot \frac{\theta_{iq}}{b_{int} b_q}
\]

Since \((T_k, FQ_k, p_q, \text{and } p_s)\) is exogenously given factors, indifference curves consist of \((\theta_{iq}, \theta_{is})\) and \((b_q, b_s, \text{and } b_{\text{int}})\) and so \(\theta_{is}\) is a function of \((\theta_{iq}, b_q, b_s, b_{\text{int}})\) conditional on \(k\).

Equation (6) shows different demand functions observed within the user group selecting plan \(k\).
\(FQC_k\) and \(GEC_k\) can be derived in the similar way \(IDC_{min,k}\) is derived. Plugging \(DF(1)\) and \(DF(2)\) for \(FQC_k\) (\(DF(2)\) and \(DF(3)\) for \(GEC_k\)) into indirect utility function in the same plan characteristics – recall that both \(FQC_k\) and \(GEC_k\) split the users selecting the same plan, the comparison enable us to get the following general functional form of \(FQC_k\) and \(GEC_k\):

\[
FQC_k \Rightarrow \theta_{iq} = \frac{FQ_k + 3b_{int}b_q b_s - FQ_k b_{int}^2 b_q b_s}{b_{int} b_q} - \frac{\theta_{iq}}{b_{int} b_q} \tag{8}
\]

\[
GEC_k \Rightarrow \theta_{iq} = \frac{FQ_k + 3b_q + 3b_{int}b_q b_s - FQ_k b_{int}^2 b_q b_s}{b_{int} b_q} - \frac{\theta_{iq}}{b_{int} b_q} \tag{9}
\]

The user grouping (15 groups from 14 indifference curves) can be illustrated as shown in Figure 4.

---

**Figure 3.4. Indifference curves and demand functions**

---

5. **Estimation procedure**

To operationalize the theoretical model, we derive a joint likelihood function. We, first, formulate the probability of choosing a plan \(k\) and then the probability of observing a real consumption bundle \((q_{ik}, s_{ik})\) conditional on the plan choice.

5.1. **Probability of choosing a plan \(k\)**

We calculate the probability of an individual \(i\)’s choosing a plan \(k\), from the fact that a user
chooses the plan that maximizes utility, conditional on the expected future consumptions (not real consumption) derived from \((\theta_{iq}, \theta_{is})\) and \((b_q, b_s\) and \(b_{int}\)). The parameters \((b_q, b_s\) and \(b_{int}\)) is to be estimated, whereas the \((\theta_{iq}, \theta_{is})\) is not observed by econometricians. We make a distributional assumption on unobserved user type (heterogeneity).

We assume that the satiation points of consumers, \(f(\theta_{iq}, \theta_{is})\), follows a truncated bivariate normal distribution: \[
\begin{pmatrix} \theta_{iq} \\ \theta_{is} \end{pmatrix} \sim TBN(\mu, \Sigma), \mu = \begin{pmatrix} \mu_q \\ \mu_s \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_q^2 & \rho \sigma_q \sigma_s \\ \rho \sigma_q \sigma_s & \sigma_s^2 \end{pmatrix}.
\]

We made the distributional assumption, referring to the plotting of the real consumptions. Since a satiation point can never be less than zero, a truncated distribution is appropriate. We assume that \((\theta_{iq}, \theta_{is})\) follow a joint normal distribution rather than independent normal distributions – i.e., we allow the correlation between \(\theta_{iq}\) and \(\theta_{is}\) to capture the unobserved inherent association of two service consumptions in addition to cross effect. Thus, if \(\rho > 0\), it indicates that the preference for voice service is positively correlated to that for SMS service. The distinction between the relationship of \(\theta_{iq}\) and \(\theta_{is}\) and the relationship of real consumptions in the two services is extremely important in our research concern. The assumption of a joint distribution allows us to examine the cross effect by excluding the impact of inherent association. The parameters \((b_q, b_s, b_{int})\) and means \((\mu_q\) and \(\mu_s\)), variances \((\sigma_q\) and \(\sigma_s\)) and correlation \((\rho)\) are the structural parameters of interest to be estimated.

Given the distributional assumption, we can write the probability of a consumer choosing plan:

\[
Pr_{ik} = \Pr(\text{plan} = k \mid \theta_{iq}, \theta_{is}) = \int \int_{D_k} f(\theta_{iq}, \theta_{is}) d\theta_{iq} d\theta_{is}
\]

, where

\[
f(\theta_{iq}, \theta_{is}) = \frac{2\pi \sigma_q \sigma_s}{1 - \rho^2} \sqrt{1 - \rho^2} \int_{-\infty}^{\theta_{iq}} \int_{-\infty}^{\theta_{is}} f(\theta_{iq}, \theta_{is}) d\theta_{iq} d\theta_{is}
\]

\[
Q = \frac{1}{1 - \rho^2} \left[ \frac{(\theta_{iq} - \mu_q)^2}{\sigma_q^2} - 2 \rho \frac{(\theta_{iq} - \mu_q)(\theta_{is} - \mu_s)}{\sigma_q \sigma_s} + \frac{(\theta_{is} - \mu_s)^2}{\sigma_s^2} \right]
\]

\[
D_k = \{IDC_{min,k}, IDC_{min,k+1}\}
\]

24 After selecting plan \(k\), they cannot change the plan while they are increasing the consumptions.
5.2. Probability of observing \((q_{ik}, s_{ik})\) conditional on \(k\)

In the second stage, consumers select a consumption bundle of voice and SMS. However, the actual demand observed would not be the same as the expected demand derived from equation (6). The difference between “real” consumption and “calculated or expected” consumption levels occur due to unobserved noise such as a period specific factor that both consumers cannot anticipate – actual consumption is to some extent out of the control of consumers. That is, the error term reflects the random shock (or measurement error) the user may experience in a given month. For empirical estimation, we add error term in demand function as an additive form following Burtless and Hausman’s (1978) approach. Here, we assume that the distribution of error terms, \(u(e_{ikt}^q, e_{ikt}^s)\), follows the bivariate normal and also that the two random terms are independent:

\[
\begin{bmatrix}
e_{ikt}^q \\
e_{ikt}^s
\end{bmatrix} \sim MVN\left(\begin{bmatrix}0 \\ 0\end{bmatrix}, \begin{bmatrix} \sigma_q^2 & 0 \\ 0 & \sigma_s^2 \end{bmatrix}\right).
\]

Assuming \(f(\theta_{iq}, \theta_{is})\) and \(u(e_{ikt}^q, e_{ikt}^s)\) are stochastically independent, the probability of observing the usage, \((q_{ik}, s_{ik})\) conditional on plan \(k\) is:

\[
g(q_{ikt} & s_{ikt} \mid k) = \frac{\int \int_{D_k} u(e_{ikt}^q, e_{ikt}^s) f(\theta_{iq}, \theta_{is}) d\theta_{iq} d\theta_{is}}{\int \int_{D_k} f(\theta_{iq}, \theta_{is}) d\theta_{iq} d\theta_{is}}
\]

5.3. Joint likelihood function

Now we can derive the joint distribution of a user \(i\) choosing the plan and then choosing \((q_{ik}, s_{ik})\) given individual \((\theta_{iq}, \theta_{is})\). The joint likelihood function for a user is \(Pr_{ik}(k \mid \bullet) \times g_{ik}(q_{ik}, s_{ik} \mid \bullet, k)\).

Any statistical or econometric model typically makes an important trade-off between using an analytically tractable, but parametrically restrictive specification, versus analytically complicated, but parametrically flexible specification (Seetharaman et al. 2005). In a similar vein, our formulation shows a vast nonlinear equation and there are also nonlinear constraints derived from (1) the concavity condition of utility function and (2) the condition of monotone ordering of indifference curves.

1. \(0 < b_{iq} b_{is} b_q < 1\)
(2) \(b_q < \frac{2}{3} \min[\theta_{is-IDC_{min,k}} - \theta_{is-FQC_k}] = \frac{2}{3} 17 \left(1 - b_{int} b_q \right)\)

where \(\theta_{is-IDC_{min,k}}\) and \(\theta_{is-FQC_k}\) indicate intercepts on the \(\theta_{is}\) axis, respectively.

We maximize the next function subject to the constraints:

\[
L = \prod_i \left( \Pr_{ijk}(\bullet) \times g_{ik}(\bullet) \right) \\
= \prod_i \left( \int_{\mathbb{D}_k} u_q \left( \epsilon_{ik}^q \right) u_q \left( \epsilon_{ik}^q \right) f(\theta_q, \theta_a) \ d\theta_q \ d\theta_a \right) \approx \prod_i \left( E_{f(\theta_q, \theta_a)} \left[ \text{Tr} \times u_q \left( \epsilon_{ik}^q \right) u_q \left( \epsilon_{ik}^q \right) \right] \right) \tag{12} \]

Log likelihood is:

\[
\ln L \approx \sum_i \ln \left( E_{f(\theta_q, \theta_a)} \left[ \text{Tr} \times u_q \left( \epsilon_{ik}^q \right) u_q \left( \epsilon_{ik}^q \right) \right] \right) \tag{13} \]

We could not obtain closed form expression for the joint likelihood function and so we had to compute it numerically. We tried to estimate the model two ways: (1) maximum likelihood estimation (MLE) with direct numerical approximation and (2) maximum simulated likelihood estimation (MSLE) using Monte Carlo methods. When we relied on MLE, we encountered a huge computational burden involved in numerical integration, so that the increase of sample size was very restricted. Here, we will show results from MSLE. When we used MSLE, we selected \(f(\theta_q, \theta_a)\) as an importance function. To sample from a bivariate normal distribution, we began with draws from two standard normal distributions and then used the Cholesky decomposition. By matrix algebra, it is possible to decompose the multivariate normal distribution in the following way,

\[
\begin{pmatrix}
\theta_{iq}^{\text{rg}} \\
\theta_{is}^{\text{rg}}
\end{pmatrix} = 
\begin{pmatrix}
\mu_q \\
\mu_s
\end{pmatrix} + 
\begin{pmatrix}
\sigma_q \sqrt{1 - \rho^2} & \sigma_q \rho \\
0 & \sigma_s
\end{pmatrix}
\begin{pmatrix}
e_{1i}^{\text{rg}} \\
e_{2i}^{\text{rg}}
\end{pmatrix}
\]

When we maximized the simulated log likelihood, we used the same set of random draws for every computation in order to achieve continuity (500 draws). That is, each observation has its own unchanging vector of 500 draws. We used the BHHH (outer product of gradients) estimator to compute the asymptotic covariance matrix of the simulated maximum likelihood estimator, based on simulation as well.
5.4. Identification issues

As the three choice decisions, \([ (k), (q_{it}, s_{it}) ] \) are the consequences of a single utility maximization for an individual, the model ensures that these decisions provide, in combination, the greatest possible utility to the individual. The parameters to be estimated in the study are grouped into two categories: (1) distribution-related parameter groups consisting of \( (\mu_q, \mu_s, \sigma_q, \sigma_s, \text{ and } \rho \text{ for satiation point distribution}, \sigma_{qit} \text{ and } \sigma_{sit} \text{ for measurement error distribution}) \) and (2) three main parameters embedded in the utility function \( (b_q, b_s \text{ and } b_{int}) \).

We have unobserved heterogeneity across individuals in the derivation of the joint probability. Each individual is expected to have a fixed value affecting the optimal consumption bundle, indirectly showing intrinsic service preferences. Thus different individuals choose a different plan choice and a different consumption bundle. The parameters in our model are, in general, identified by systematic variation in plan choice and consumptions given plan choice across individuals. Parameters relating to distributional assumptions can be identified through the maximization of joint likelihood conditional on a plan choice. The key parameters \( (b_q, b_s \text{ and } b_{int}) \) can be estimated through not only likelihood maximization but also the variation of plan choice – the unique pricing scheme causing kinked budget constraint allows us to identify them. And also, the model formulation enables us to capture the cross effect, by allowing the intrinsic preference to wireless services to be distributed across individuals – the model allows for the dependency of two services in the decisions in terms of both inherent association and cross effect.

6. Result and discussion

The estimation results are given in Table 3. We first estimate our model without incorporating demographics (see the first column of Table 3). One of our key interests is the sign of \( b_{int} \). The negative and significant \( b_{int} \) provides the evidence that voice and SMS form a substitutive relationship. This finding give us several insights: (1) the real consumption levels, which we can observe, are less than the
satiation points, which we cannot see, in both services, (2) the optimal consumption level in voice (or SMS) decreases as the consumption of the other service goes up because the consumption in one service partially satisfies the satiation points in the other service, and (3) the optimal consumption level in voice service decreases through the introduction of SMS.

The intrinsic association between satiation points in the two services is highly significantly positively related ($\rho = 0.845$). That is, this shows that a heavy user of one service is likely to be a heavy user of the other service regardless of substitution or complementary effect. Compared to the correlation of two services in terms of real consumptions of voice and SMS (around 0.2), the estimated $\rho$ is very high. Given that, we can infer that if one does not reflect on the impact of the intrinsic association of two services – controlling the noise –, one would get the biased result of the relationship between real consumptions in the two services (cross effect) due to the influence of inherent association.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>G1 Age&lt;30</th>
<th>G2 Age=[30,40)</th>
<th>G3 Age&gt;=40</th>
<th>S0 Female (0)</th>
<th>S1 Male (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b_{int}$</td>
<td>-0.316** (0.064)</td>
<td>-0.501** (0.114)</td>
<td>-0.494** (0.117)</td>
<td>-0.343* (0.149)</td>
<td>-0.598** (0.183)</td>
<td>-0.311** (0.030)</td>
</tr>
<tr>
<td>$b_q$</td>
<td>7.429** (1.230)</td>
<td>5.003** (0.630)</td>
<td>8.672** (3.488)</td>
<td>9.039** (3.316)</td>
<td>7.715** (2.828)</td>
<td>8.429** (0.613)</td>
</tr>
<tr>
<td>$b_s$</td>
<td>0.124** (0.026)</td>
<td>0.053** (0.015)</td>
<td>0.061** (0.017)</td>
<td>0.107* (0.048)</td>
<td>0.049** (0.015)</td>
<td>0.095** (0.010)</td>
</tr>
<tr>
<td>$\mu_q$</td>
<td>285.913** (1.364)</td>
<td>331.008** (3.167)</td>
<td>292.378** (5.086)</td>
<td>213.764** (3.613)</td>
<td>290.005** (1.731)</td>
<td>277.108** (1.620)</td>
</tr>
<tr>
<td>$\mu_s$</td>
<td>11.058** (0.323)</td>
<td>16.004** (0.474)</td>
<td>11.544** (2.779)</td>
<td>11.207** (0.641)</td>
<td>14.662** (0.288)</td>
<td>9.000** (0.198)</td>
</tr>
<tr>
<td>$\sigma_q$</td>
<td>137.298** (1.258)</td>
<td>171.793** (7.383)</td>
<td>107.328v (18.458)</td>
<td>142.302** (4.416)</td>
<td>130.098** (2.332)</td>
<td>143.286** (1.237)</td>
</tr>
<tr>
<td>$\sigma_s$</td>
<td>26.603** (0.117)</td>
<td>25.854** (0.190)</td>
<td>19.534** (0.050)</td>
<td>18.039** (0.311)</td>
<td>23.094** (0.059)</td>
<td>21.803** (0.051)</td>
</tr>
<tr>
<td>$\sigma_{eq}$</td>
<td>205.520** (0.158)</td>
<td>206.955** (0.140)</td>
<td>179.360v (0.527)</td>
<td>158.809** (0.539)</td>
<td>184.651** (0.071)</td>
<td>197.845** (0.135)</td>
</tr>
<tr>
<td>$\sigma_{es}$</td>
<td>18.888** (0.003)</td>
<td>25.196** (0.010)</td>
<td>12.055** (0.004)</td>
<td>13.621** (0.008)</td>
<td>18.911** (0.004)</td>
<td>14.124** (0.003)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.845** (0.005)</td>
<td>0.847** (0.016)</td>
<td>0.860** (0.036)</td>
<td>0.644** (0.026)</td>
<td>0.830** (0.014)</td>
<td>0.676** (0.006)</td>
</tr>
<tr>
<td>$N$</td>
<td>10,000</td>
<td>3695</td>
<td>4986</td>
<td>1319</td>
<td>5462</td>
<td>4538</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-97911</td>
<td>-38648</td>
<td>-48257</td>
<td>-14037</td>
<td>-53269</td>
<td>-44684</td>
</tr>
</tbody>
</table>

Standard errors are shown in parentheses.
*Significant at $p < 0.05$  **Significant at $p < 0.01$

Table 3.3. Estimated parameters

We next split the data based on demographic factors (age and gender) and analyze the difference
of the key parameters across sub-groups. The results are shown from column 2 to column 6. We observe some variation of estimated parameters across either age or gender.

Younger users, on average, have higher \((\theta_{iq}, \theta_{is})\) in both services. We found a stronger substitution effect in the younger group than the older group. Two price response parameters are both significant in all groups. Since \(b_{q}\) is significantly greater than \(b_{s}\), we can see that the voice consumption is more sensitive to price change. We will discuss the implication of the two price response parameters in detail with calculated own- and cross-price elasticity.

6.1. Estimated own- and cross-price elasticities

We calculate own- and cross-price elasticities based on the DF3 in equation (6) – the marginal price of voice is not included in both demand function (1) and (2) –, relying on invariance characteristics of MLE. They appear in Table 4, where we calculate the elasticities at the mean values in both services and at the marginal price information – e.g., \(\epsilon_q = -\frac{3b_{im}b_{q}b_{s}}{b_{im}b_{q}b_{s}}\). The reaction to proportional price changes will be quite different depending on whether prices are high or low (or equivalently the elasticity depends on consumed quantity in a linear demand function). Given the substitution effect \((b_{im} < 0)\), the own-price elasticities are negative and the cross elasticities are positive. Several interesting results emerge from Table 4.

<table>
<thead>
<tr>
<th>Mean-usage price elasticity</th>
<th>Whole Sample</th>
<th>G1: Age &lt;30</th>
<th>G2: 30&lt;=Age &lt;40</th>
<th>G3: Age&gt;=40</th>
<th>S0: Female</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Voice</td>
<td>SMS</td>
<td>Voice</td>
<td>SMS</td>
<td>Voice</td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>Own-price elasticity</td>
<td>Cross-price elasticity</td>
<td>Mean</td>
<td>Own-price elasticity</td>
</tr>
<tr>
<td>Voice</td>
<td>285</td>
<td>-0.08614</td>
<td>0.07403</td>
<td>330</td>
<td>-0.04875</td>
</tr>
<tr>
<td>SMS</td>
<td>13</td>
<td>-0.03149</td>
<td>0.00338</td>
<td>17</td>
<td>-0.01010</td>
</tr>
</tbody>
</table>

71/153
Table 3.4. Estimated own- and cross-price elasticities

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Own-price elasticity</th>
<th>Cross-price elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voice</td>
<td>287</td>
<td>-0.09327</td>
<td>0.05614</td>
</tr>
<tr>
<td>SMS</td>
<td>14</td>
<td>-0.01217</td>
<td>0.00274</td>
</tr>
<tr>
<td>S1: Male</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Voice</td>
<td>274</td>
<td>-0.10006</td>
<td>0.08123</td>
</tr>
<tr>
<td>SMS</td>
<td>10</td>
<td>-0.03097</td>
<td>0.00296</td>
</tr>
</tbody>
</table>

(1) Comparison between wireless demand and fixed line demand

The estimated own price elasticity of voice demand is small compared to what has been shown in a fixed-line phone demand. According to Kling and Ploeg (1990) and Park et al. (1983), the price elasticity of fixed phone service is in the range of -0.1. Our estimates show that users are less sensitive to price in mobile voice service than fix-phone voice service. The low number could also be the reflection of the fact that users always carry mobile service equipment. Another possible explanation is that mobile communication is thought to be an indispensable communication tool and the value of wireless communication service is perceived as if it is a necessity.

(2) Comparison between voice demand and SMS demand

SMS service is far less elastic than voice service in own-price elasticity by about 3 times. One explanation is that the specific value of SMS service exists and users perceive SMS service as an invaluable communication tool, even if the consumption level is small. But it is quite possible that this result comes from a relatively small consumption because the price elasticity is calculated with not only price response parameters but also average usage.

One interesting thing is an asymmetric pattern in cross-price elasticities. Price changes of SMS service have a larger effect on voice service than the other way around. In particular, cross-price elasticity of SMS demand is extremely low (0.074 vs. 0.003 by about 20 times). Given that, we can infer that users perceived voice service as the key (primary) communication tool even if there is a substitute effect.

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25 Here, “asymmetric pattern” indicates that the magnitude is not identical. The directions are the same.
26 There could be a scaling problem in the interpretation (minutes vs. message).
(3) Comparison based on demographics

The results show that the price elasticities are different both across groups segmented by age as well as across male and female gender groups. The findings of big variation of price elasticity across individual demographic profiles could be informative for practical managerial implication. First, we find that the younger users are, on average, more inelastic than the older group in four kinds of elasticity (own-and cross vs. voice and SMS). We do not have information regarding individual income. But, it is generally believed that the older users have a higher income and they are expected to be more inelastic to price change. Therefore, this is somewhat counter intuitive and gives some unique insight in understanding mobile service. Second, the cross-price elasticity of voice demand in group 1 is far lower than those in other groups. Therefore, we conclude that when the marginal cost of SMS increases, the older users are more likely to change the communication tool from SMS to voice than the younger are. Third, female users are more inelastic than male users in SMS service while there is not a big difference in voice elasticity. And the cross-price elasticity of voice demand in the female group is lower than those in the male groups. In particular, the cross-price elasticity of voice service in the male group is the highest figure in Table 4. We can infer that when the marginal cost of SMS increase, men are more likely to change the communication tool from SMS to voice than the women are.

6.2. Evidence of substitution effect based on consumption bundle

We perform regression analysis on the data in order to acquire another evidence of substitute effect. When the users are satiated below free minutes, they face zero marginal cost for voice services but positive marginal cost for SMS. Once free quote exceeds, the voice minutes also incur a marginal cost per minute. If we can find significant jump of the SMS consumption before and after the free quota, it will be the evidence of substitution effect based on the fact that the increment of marginal cost from 0 to 3 in voice service induces the SMS consumption replaced by voice service. We run the following regression:
\[ s_i = \beta_0 + \beta_1 q_i + \beta_2 D_{FQ_k} + \beta_3 (q_i - FQ_k)^+ + u_i \] (14)

where
\[ D_{FQ_k} = 1 \text{ if } q_i \geq FQ_k, \text{ otherwise } 0. \]

\[ (q_i - FQ_k)^+ = q_i - FQ_k \text{ if } q_{ik} \geq FQ_k, \text{ otherwise } 0 \]

We examined the change of SMS consumption at 350 minutes in both groups (one selecting plan 1 and the other selecting plan 2) – the majority of users selected plan 1 (around 94.6%) and the free minute of plan 1 is 350 minutes –. We confirm that there is an abrupt increase of SMS consumption at the kinked point in only the user group selecting plan 1 based on significant coefficient of dummy \( D_{FQ_k} \) only for the user group 1.

<table>
<thead>
<tr>
<th>User Group selecting Plan 1</th>
<th>User Group selecting Plan 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voice</td>
<td>0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>( D_{FQ_k} )</td>
<td>1.031*</td>
</tr>
<tr>
<td></td>
<td>(0.543)</td>
</tr>
<tr>
<td>( (Voice - 350)^+ )</td>
<td>.0129***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Constant</td>
<td>6.973***</td>
</tr>
<tr>
<td></td>
<td>(0.382)</td>
</tr>
<tr>
<td>N</td>
<td>56634</td>
</tr>
<tr>
<td>R-square</td>
<td>0.0113</td>
</tr>
</tbody>
</table>

Standard errors are shown in parentheses
*Significant at \( p < 0.05 \)  **Significant at \( p < 0.01 \)  ***Significant at \( p < 0.001 \)

Table 3.5. Regression result

We tested the same model in the narrower range of voice consumption: \( q_i = [150, 550] \). The dummy is still significant, providing stronger evidence of substitution effect.

![Figure 3.5. Substitution effect of SMS for voice service](image)
6.3. Policy Experiments

With the estimated structural parameters, the managers can now perform what-if analysis. That is, we can analyze what happens to a firm’s demand and hence profits “if an entering fee increases by 1%” or “if the firm decreases a given free minutes by 1%.” Through this experiment, we can predict the impact of the change of the entering fee, which was not examined in our model specification, in addition to the marginal price elasticity estimated. However, there is a limitation in the experiment. In a competitive market, customers can respond to the change of a pricing scheme by leaving the company (switching firms). But, in this experiment, we assume that (1) consumers do not change the company – i.e., the switching cost of telephone companies is very high – and (2) consumers can switch among the entire (modified) menu of plans, due to inability to obtain the information concerning consumer’s behavior of firm switch and the pricing scheme available in other firms.

But, conducting policy experiments that capture the effects of change in the strategic pricing scheme – pricing is an essential element of strategy and firms are always concerned with the ramifications of changes to their pricing scheme –, we can search for the most effective strategy to increase the firm’s profit. That is, while predicting the effects of a price change is a challenge, our model based on a structural framework allows us to simulate the effects of change of pricing. Given that, we simulate the effects for (1) the price changes of marginal cost and (2) the price changes of the entering fee and (3) the change of free minutes on firm’s revenue and compared them.

<table>
<thead>
<tr>
<th>Change of pricing</th>
<th>Marginal Cost of both services</th>
<th>MC of voice</th>
<th>MC of SMS</th>
<th>Fixed Cost (entering fee)</th>
<th>Free Minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase of 10%</td>
<td>Increase of 10%</td>
<td>Increase of 10%</td>
<td>Increase of 10%</td>
<td>Increase of 1%</td>
<td>Decrease of 1%</td>
</tr>
<tr>
<td>Increase of 0.46%</td>
<td>Increase of 0.20%</td>
<td>Increase of 0.31%</td>
<td>Increase of 0.90%</td>
<td>Increase of 0.43%</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.6. Simulation of change of pricing scheme

As shown in Table 6, the changes in entering fee have a greater impact on the firm’s revenue than other pricing change. In particular, the decrease of free minute can increase the revenue but the increase was less than that of the entering fee by around half – the increase of fixed cost by 1% is comparable to
the increase of the marginal cost of both services by 1%. And, the changed revenue varies depending on which service the firm increases marginal cost in. The change in marginal prices of SMS service have a bigger influence on the revenue than that of voice service, which is consistent with the inference from the calculated price elasticity of demand.

7. Conclusion, limitation and further research direction

We provide a general methodology to construct an estimable structure which takes into account the sequential nature of consumer decision making, nonlinear pricing commonly observed in wireless service consumption, and the consumption of two distinct services. We estimate the model with a unique and rich individual level data. In particular, we estimated “real” substitutive impact by controlling the inherent association of two services with conceptual framework of user types (satiation points).

Our results show that voice and SMS services substitute each other and the substitution effect was confirmed with the regression model based on real consumption. We also find that price elasticities in wireless communication demand (-0.086 for voice and -0.031 for SMS) are a little less than what has been observed in landline phones where many researchers have reported elasticities in the range of -0.1 to -0.2. We also explore how user sensitivity varies depending on demographic characteristics. We find that older users are more price sensitive and that there is little difference between the consumption patterns of males and females. The extent of substitution effect and price elasticity somewhat depends on users’ demographic factors. The distinction of the inherent association and the price elasticities could be very informative for practical managerial implication such as optimal pricing scheme. Through policy experiments, we found that the tactical change of entering fee is most effective in increasing firm’s profit.

Although our findings in the cross effect of two mobile services are meaningful in theory and practice, the uniqueness of our data – regional or time – might prohibit the generalization of the finding. Thus, our research provides avenues for future research by collecting data from a different region and a more recent data set. And this weakness can be supplemented in future research by replicating it with a different data. Then we believe that individual level analysis would be better than analysis on the
aggregated level because of the existence of inherent association of two services. When future studies analyze the cross effect on the aggregate level, they might have to pay attention to the noise from the inherent association.

We cannot observe the budget allocated to mobile service as well as (disposable) income. Therefore, our analytical framework doesn’t reflect on how individual users allocate their monthly budget to mobile communication and outside goods. In reality, users are expected to make decisions of budget allocation by comparing the utility from mobile service and that from the others. For example, users with very low satiation points might not even pay the lowest fixed fee for mobile service, giving up using mobile service. Given that, truncation lines would not be $\theta_iq = [0, \infty], \theta_{iu} = [0, \infty)$, but a particular line under cross effect. Similarly, one can analyze the model with another distributional assumption. For example, the satiation points can be assumed to be log-normal instead of truncated bivariate normal.

We assume that satiation points of two services are interdependent through a truncated bivariate normal structure. However, we can not answer how two services are interrelated, or on which dimension they are interdependent. Furthermore, future study can decompose users' heterogeneity based on other observables. Such specification may result in a more powerful model that better incorporates users' heterogeneity, as well as extending its predictive power to forecast substitutive and complementary relationships among services. In a similar vein, users’ utility maximization critically depends on satiation points as well as other parameters in our model. Although we find there is some variation across segmented groups, we cannot explain how the satiation points are established. This could be very interesting topic for future research.

Even if our simulation shows that changing the entering fee is the best way to increase profit, we could not examine exactly either free minute elasticity or entering cost elasticity, which would be an interesting topic in the wireless demand structure. As shown with the fixed line (Train et al. 1987), it is possible that the price elasticity for the monthly fixed charge is higher than the price elasticity for the marginal charge – which is closely related to consumers’ firm switching behaviors.

Our current work is focused on Voice and SMS in mobile service. Future work should analyze
other service such as WAP (Wireless Application Protocol). Actually, nowadays, subscribers of mobile service can access WAP service. WAP is typically used diversely: accessing email, getting a stock quote or any other information. So, it leaves us with another interesting empirical question, “Does WAP substitute voice service as well?”
Chapter 4: On Product-level Uncertainty and Online Purchase Behavior: An Empirical Analysis

Abstract

The advantage of business-to-consumer (B2C) commerce based on Information Technology (IT), has resulted in the establishment of many Internet shopping malls (ISMs). This study is motivated by the fact that there are two kinds of uncertainty embedded in online shopping: (1) uncertainty relating to virtual retailer (ISM) and (2) product-level uncertainty induced from the omission of physical investigation. Given that, this study examines a product-level uncertainty reduction model in two dimensions: (1) product attribute (tangibility level) and (2) price. Our analysis shows several primary empirical results. First, for the product spectrum in terms of tangibility level, online consumers are likely to purchase products with more intangible attribute as they increase online shopping experience. Second, this uncertainty reduction process is contingent on the product price. In very cheap and expensive product lines, shopping experience cannot induce the purchase of more intangible items, while the relationship is statistically significant in the moderate price range, ($50,$150). Given that, we can infer that online consumers don’t regard the product uncertainty due to missing of physical investigation very highly if the price of a product is relatively cheap and that individual shopping experience cannot overcome the product-level uncertainty in the case of expensive products. Third, ISM’s uncertainty reduction strategies: (1) introduction of the reputation established in the offline market and (2) the digitalization of commercial film, turn out to be effective tool in terms of induction of the purchase of intangible products. Moreover, two strategies work even in expensive product lines. The impact of reputation transfer is equivalent to around 150 purchase of online shopping experience. The impact of vivid informative channel is equivalent to 57 purchase of online shopping experience. We found that online shoppers are inclined to trust the indirect experience (or social learning, reputation transfer) associated with off-line world more than virtual experience, even if they shop in the online world. Fourth, another interesting finding is that there is asymmetric expansion of product spectrum in terms price. In summary, consumers have tendency to expand the spectrum strongly toward cheaper product and weakly toward highest product. And the expansion toward the cheaper product is directly induced by online shopping experience and one toward expensive items comes from only the indirect effect of the number of transactions. Finally, the number of online transactions in a unit of time is positively affected by online shopping experience and the number of transactions in a unit of time plays a mediating role of the relationship between online shopping experience and highest price. Theoretical and practical implications are discussed.

Key words: Online shopping; product-level uncertainty; Informative channels comparison; Reputation transfer; Digitization of commercial film; product spectrum
1. Motivation

“For the first time since online retailing was born a decade ago, the sales of clothing have overtaken those of computer hardware and software, suggesting that consumers have reached a new level of comfort buying merchandise on the Web. In 2006, revenue from skirts, suits and shoes reached $18.3 billion, surpassing that from PCs, printers and word-processing programs, which totaled $17.2 billion, according to a report to be released today by a major trade group.” in the article of “Less Risk Seen in Purchasing Clothes Online” by Michael Barbaro of The New York Times, dated May 14, 2007.

It is widely recognized that consumers have to contend with uncertainty when they engage in online commerce. A rich literature on online trust has developed with a focus on uncertainty as it pertains to various attributes of the vendor (e.g., its perceived and revealed trustworthiness and its operational excellence.) Previous studies on “online trust” have been devoted to the illustration of the mechanism of the online trust development between online retailers and consumers, examining the essence (or antecedents) of online consumers’ trust building (Bakos 2001; Bart et al. 2005; Gefen et al. 2003; Grabner-Kräuter and Kaluscha 2003; Jarvenpaa et al. 2000; Kim and Benbasat 2006; Kim et al. 2004; Kong and Hung 2006; Lim et al. 2006; McKnight et al. 2002; Pavlou and Gefen 2004; Shankar et al. 2002; Torkzadeh and Dhillon 2002). In addition to this work on online trust, there is a large literature focused on online shopping behavior. This work analyzes the effect from an economic standpoint of factors such as (1) the lowered search cost, (2) price dispersion across vendors, (3) price elasticity in the online market, and (4) online differentiation strategies (Baye et al. forthcoming; Brynjolfsson and Smith 2000; Clay et al. 2002; Clemons et al. 2002; Lynch and Ariely 2002).

In this paper we address product-level uncertainty – a uncertainty that is present when a customer assesses a product for purchase in an online environment. Product-level uncertainty arises from the inability of customers to physically examine and experience the product that they would like to or intend to purchase. The importance of product-level uncertainty is supported by the recent study showing the importance of physical investigation. Peck and Wiggins (2006) shows that the marketing implications of touch (here physical investigation) are more substantial than previously believed – touch has a persuasive
effect only if it provides attribute or structural information about a product – because a communication that incorporates touch can lead to increased affective response and increased persuasion whether a consumer is motivated by touch or not.

Recognizing the importance of product-level uncertainty, online firms have sought to reduce such uncertainty by experimenting with alternative ways of packaging and presenting product information to customers. These range from the use of text and images to video (such as seen in home shopping channels on Cable TV). This leads to a fundamental question – how does the manner and type of product information presented affect consumers’ willingness to make choices without the experiential information of the product in the online purchase environment? How are these purchase choices affected by reputation established by offline operations of the vendor?

We examine these questions using a unique data set consisting of all purchase transactions conducted between January 2002 and June 2006 (around 4 and half years) from the leading Korean Internet Vendor Hyundai HMall. Prior work in the literature used at most three or fewer product categories and focused on homogeneous and structured goods – e.g., books: (Ancarani and Shankar 2004; Clay et al. 2002; Smith and Brynjolfsson 2001), computer memory: (Ellison and Ellison 2004), and consumer electronics: (Baye et al. 2004). In contrast, we examine consumers’ purchasing behavior across the whole spectrum of products available at a “general” retailer covering various product categories (2333 categories defined in this study). The expansion of the product spectrum was deliberately designed even at the stage of looking for a data source in order to enable us to analyze the longitudinal change of consumers’ online shopping behavior as it related to product-level uncertainty – in particular, the change in the categories of products that individual consumers purchase, which is related to the point in the article quoted at the very beginning of this paper, and the change in the price spectrum of products purchased from the online vendor.

The rest of this paper is organized as follows. We describe the research site in section 2. In section 3, we build an analytic channel choice model of online vs. offline purchasing accounting for

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27 One unique study examining relatively unstructured products (wine shopping mall) is article by Lynch and Ariely (2002).
product-level uncertainty and derive specific testable research hypotheses. We specify our estimation model in section 4 and describe the data and present the empirical results in the subsequent section. Finally, we conclude with a summary of our findings, robustness checks, limitation, and suggestions for future research.

2. Research Site

Our research site (www.hmall.com) is one of the premier online vendors in Korea. It has a unique structure in the provision of product information on the Web, which is attributed to the evolution of the mother company – Hyundai Department Store Co., Ltd (HDS)\(^28\) – and its strategy to achieve synergy from diversified channels at a corporate level.

HDS started business as an offline physical retailer (hereafter, called department store, DS) around 35 years ago and DS has been the core (retailing) business for HDS since then. DS is a full-line department store with upscale apparels, fashion goods, home furnishings, food, and electronics. It is a highly reputable and branded high-end department store in Korea. Leveraging the competitive edge that HDS has gained in the retail industry through the operation of DS and as a retail channel diversification (extension) strategy, HDS launched TV home shopping business (Hyundai Home Shopping) in November 2001. The online retail business of HDS first began selling online in 1997 as a cyber shopping team and was re-launched and upgraded in 2002 as Hmall.com.

Given the organizational structure of HDS, Hmall has been selling not only self-procured products but also products supplied from the other two channels – (1) DS (Department store) and (2) HS (Home Shopping) – in the online market since 2002, by playing the role of Internet retailing agent in HDS. Hmall utilizes the strength of the DS and HS channels. First, when Hmall displays the products supplied from DS (hereafter called ISM_DS) on the Website, it accentuates the source of products such as “this product is being sold in Hyundai Department Store” to leverage the reputation of DS. Second, Hmall

\(^{28}\) It is the division in charge of retail business in Hyundai enterprise.
digitizes commercial video developed by Hyundai Home Shopping and enables consumers to access the video promotions on the Web for the products supplied by HS (hereafter called ISM_HS).

From the customers’ standpoint, the set of product information available for products labeled ISM (products procured by Hmall for sale online), ISM_DS (products from the DS sold online), or ISM_HS (products from the HS sold online) is different. First, in the products of both ISM and ISM_DS, only text and image information (including a little virtual demonstration to some extent) are provided on the Web. But, Hmall differentiates ISM_DS from ISM by specifying “products being sold at DS”. In addition to both text and image, the products of ISM_HS are accompanied with video commercial showing product demonstration along with show hosts and/or models (e.g., product trial). As a consequence, there are three different methods for communicating product information, which are employed in our research site (see

![Three information communication methods](image)

![Conceptual Definition](image)

Three information communication methods

ISM: Both text and image (a few products with multi-dimensional image)

ISM_DS: Both text and image and Accentuation of DS-produced product

ISM_HS: Video commercials in addition to both text and

Conceptual Definition

General on-line shopping behavior (Baseline product-level uncertainty reduction model)

Making use of reputation of offline established retailer (Impact of the reputation transfer)

Showing digitized commercial video (Impact of vivid demonstration)

Figure 4.1. Research site

As we mentioned, online consumers have to accommodate two kinds of uncertainty in their online purchasing decision. We have to exclude the effect of retailer-relating uncertainty in order to capture the impact of the product-level uncertainty on the online purchasing decision. The data we have collected permit us to estimate the influence of product-level uncertainty from the compounding uncertainty since our data site Hyundai Hmall is one of the most reliable and reputed online vendors in
Korea. We confirmed it through interviews with Korean online shoppers. Most interviewees said that retailer-related uncertainty such as illegal misappropriation of a credit card does not basically affect their online purchasing decision at Hmall. Some of them said that it has brand and status similar to that of Amazon.com in the United States. Furthermore, Hmall has “consumer purchasing safety policy”. According to the policy, consumers will be reimbursed their expenses when there are some problems on the retailer side such as wrong delivery. These facts lead us to believe that consumers face little to no retailer-related uncertainty while shopping at Hmall.

The data we have collected about products offered through the different information communication channels/mechanisms (ISM, ISM_DS and ISM_HS) show that each of these channels features a wide variety of products but same products are not available on any two channels. In other words, each channel features a unique set of products with no overlap in the products sold through these different channels. Interviews with managers reveal that the firm has followed this strategy in order to minimize cannibalization between these channels (Brynjolfsson et al. 2003; Kim et al. 2002; Rangaswamy and Bruggen 2005). The product differentiation strategy adopted by HDS is implemented on a specific product level (neither brand nor manufacturer level), so that three channels sell different products of the same brand. For example, among digital cameras manufactured by SAMSUNG electronics, model 1 (e.g., VLUU L77) is being sold in ISM while model 2 of brand A (e.g., VLUU I7) is being sold in HS – they are different in terms of specification, design, price and so on. And also, we found out that products from one channel are not systematically superior to or more appealing than those from another channel. The decision of procuring a product is mainly determined by category managers of each channel. Then, their negotiation skills and the first mover advantage are substantial in procuring potential products. And most category managers have regularly rotated through the three retailing channels under a job rotation policy – this is very common because all three channels are subordinates of HDS and it occurs every December. As a result, the procurement procedure associated with category managers are not expected to induce systematic product heterogeneity in terms of quality products across channels. However, there is systematic difference in product price spectrum across channels. For example, Home
shopping (HS) tends to handle more expensive products than the other channels due to its inherent expensive cost structure of broadcasting. As a result, the products advertised with digitized video commercial at Hmall are, on average, more expensive, and so we need to examine the possible product heterogeneity in the price range across channels.

3. Analytical Framework and Hypothesis Developments

In this section, we consider a general model in which a consumer \( i \) purchases products of interest sequentially in each of \( T \) discrete periods of time where \( T \) is finite. Almost all previous work regarding consumer purchasing behavior assume that consumer (indirect) utility or surplus can be approximated as a linear (or exponential) function of the product quality (positive sign) and price (negative sign) (e.g., Mehta et al. 2003). Given that the utility individual \( i \) expects to obtain from consuming a product \( p \) at the unit of time \( t \) in offline market is:

\[
E[U_{ipt}^{\text{Physical}}] = E[q_{ipt}] - price_p
\]  

(1)

Consumers are more uncertain about the expected quality due to the omission of physical investigation in the online market than the physical market. We assume that the expected utility is adequately approximated by an additive (or multiplicative) compensatory multi-attribute utility model based on the elements of information set – decision-making under uncertain environments are often modeled with information set in previous studies (Erdem and Keane 1996; Mehta et al. 2003). Let \( A_{it} \) denote the information set of consumer \( i \) at time \( t \). \( E[U_{ipt}^{\text{Online}} | A_{it}] \) is known to a consumer \( i \) at time \( t \) because every consumer knows their \( A_{it} \) at a current time period \( t \) (i.e., the state of consumer \( i \) at time \( t \) is fully characterized by the information set). The expected utility from online shopping may vary depending on the dynamic change (modification) in the elements of the individual information set with respect to even the same product. In this study, we incorporate the following four constructs as elements of individual information set (refer to the online appendix for the theoretical background of the selection

\[29\] Here, both utility and quality are expected values because this study is analyzing consumers’ purchasing decision, not realized utility (or perceived usefulness) measured after the usage of products.
of the constructs and the details of associated literature):

(1) “The proportion of (Internet-based) intangible attributes, \( \delta_p \)” indicates the extent to which information of a product can be digitally transferred (or how critical the loss of physical cue is). Equivalently, intangibility level measures the measure of the difficulty encountered by an online consumer in assessing the fit between his or her requirements and the features of a product (Degeratu et al. 2000; Kamakura and Russell 1993; Lal and Sarvary 1999; McCabe and Nowlis 2003). We assume that the proportion of each product is distributed in the interval of \([0,1]\) in our analytic model (e.g., a digital product if \( \delta_p = 0 \)).

(2) “Net benefit created from ISM, \( B_{\text{net}} \) (Bakos 1997; Keeney 1999)” denotes the comparative benefit of online shopping – calculated from “the benefit created from online shopping minus opportunity cost of online shopping” –, compared to conventional store. Because consumers considering online shopping rather than physical shopping have a positive \( B_{\text{net}} \), we assume that this variable plays a role in increasing consumer tolerance, thereby increasing consumer surplus in online shopping.

(3) “The consumer’s tolerance for product-level uncertainty” denotes the “consumer’s tolerance for uncertainty of expected quality generated due to internet-based intangible attribute,” which corresponds to “consumer’s intensity of risk aversion behavior to purchasing a product without physical investigation.” The key idea of the proposed construct is that even though a consumer can confirm the expected quality in the tangible part of a product (e.g., size and color), the consumer are still uncertain about the expected quality of the intangible part (e.g., feeling and fitness based on direct physical investigation), unless \( \delta_p \) is zero. We assume that consumer tolerance is positively affected by online shopping experience (\( \text{Exp}_{\text{it}} \)), net benefit created from ISM (\( B_{\text{it}} \)), ISMs’ marketing mix (\( j \)) to reduce product-level uncertainty, and calendar time (\( t \)) – \( \theta_0(\text{Exp}_{\text{it}}, B_{\text{it}}, j, t, u_0) \), where \( u_0 \) is a random variation –. We assume that it is distributed in the interval of \([0,1]\) in our analytic model. When calculating the expected utility in online market, \( E[U_{\text{Online}}^{\text{Values}} | A_0] \), we multiply consumers’ tolerance to the expected

---

30 The corresponding measurement (\( ILp \)) for our empirical analysis is using a five-point Likert-scale.
quality from intangible attribute. Given that, the product-level uncertainty is modeled as “$\theta_i(E_{\text{Exp}} \cdot B_{it} \cdot j, t, u_i) \times \delta_p$.”

(4) “Retailer’s brand awareness, $\eta$ (Brynjolfsson and Smith 2000; Smith and Brynjolfsson 2001)” can be designated according to online retailers’ relative branding, awareness, and trust. Since retailer-relating uncertainty affects the whole expected quality of a product (consider a wrong delivery), $\eta$ is multiplied to expected quality. We assume that it is distributed in the interval of [0,1]. The symbols used throughout the paper and the variables they represent are listed on Table 1.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>Consumer index</td>
</tr>
<tr>
<td>$j$</td>
<td>0=ISM, 1=ISM_DS, and 2=ISM_HS: classification of informative methods</td>
</tr>
<tr>
<td>$t$</td>
<td>Period when a consumer purchases a product (calendar time)</td>
</tr>
<tr>
<td>$p$</td>
<td>Product index</td>
</tr>
<tr>
<td>$E[U_{ipt}]$</td>
<td>Consumer surplus of consumer $i$ at time $t$ from product $p$</td>
</tr>
<tr>
<td>$E[q_{ipt}]$</td>
<td>Expected quality of consumer $i$ at time $t$ from product $p$</td>
</tr>
<tr>
<td>$A_{it}$</td>
<td>The information set of consumer $i$ at time $t$</td>
</tr>
<tr>
<td>$\delta_p$</td>
<td>The proportion of intangible attributes of product $p$, [0,1]</td>
</tr>
<tr>
<td>$B_{it}$</td>
<td>Net benefit created from ISM of consumer $i$ at time $t$</td>
</tr>
<tr>
<td>$\theta_{it}$</td>
<td>Consumer’s tolerance of consumer $i$ at time $t$, [0,1]</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Retailer’s brand awareness, [0,1]</td>
</tr>
<tr>
<td>$\text{Exp}_{it-1}$</td>
<td>Cumulative number of online transactions of consumer $i$ through time $t-1$</td>
</tr>
<tr>
<td>$Q_{jt}$</td>
<td>The number of transactions of consumer $i$ in channel $j$ at a unit of time $t$</td>
</tr>
<tr>
<td>$N_{it}$</td>
<td>Number of online transactions individual $i$ at time $i$</td>
</tr>
<tr>
<td>$D_i$</td>
<td>Informative method dummy, $D_0$ = ISM, $D_1$ = ISM_DS, $D_2$ = ISM_HS</td>
</tr>
<tr>
<td>$\text{Category}_p$</td>
<td>Product category of product $p$: 2333 product categories classified</td>
</tr>
<tr>
<td>$\text{IL}_p$</td>
<td>Intangibility level of product $p$</td>
</tr>
<tr>
<td>$\text{AIL}_{ijt}$</td>
<td>$31\sum\sum\sum(i=0; p=1; IL_{ijt})/\sum\sum\sum(O_{jt})$</td>
</tr>
<tr>
<td>$\text{APrice}_{it}$</td>
<td>$\sum\frac{\text{Price}_{it}}{N}$</td>
</tr>
<tr>
<td>$\text{HPrice}_{it}$</td>
<td>$\max[\text{Price}<em>{1t}, \text{Price}</em>{2t}, ..., \text{Price}_{N_t}]$</td>
</tr>
</tbody>
</table>

Table 4.1. Variables and operational definitions

The expected utility in online shopping is specified as:

$$E[U_{ij}] = E[U_{ij}^{\text{Online}}(\theta_i(E_{\text{Exp}} \cdot B_{it} \cdot j, t, u_i), \eta, \delta_p; \text{price}_p)]$$

$$= \eta \left( (1 - \delta_p)E[q_{ipt}] + \theta_{it}(E_{\text{Exp}} \cdot B_{it} \cdot j, t, u_i) \delta_p E[q_{ipt}] \right) - \text{price}_p$$

(2)

31 There is added subscript $j$ in the AIL, because we compare the effect of informative methods on AIL (to be discussed in detail).
After a consumer makes a decision to buy a product, then the consumer needs to decide where to buy the product: online market vs. physical store. Given individual’s purchasing decision of a product at time \( t \), the channel choice decision of online vs. offline is formulated as:

\[
\begin{align*}
\text{Max} & \left[ E[U_{ipt}^{\text{Online}}], E[U_{ipt}^{\text{Physical}} | A_{it}] \right] \\
\text{Consumers will buy the product online if} & \quad E[U_{ipt}^{\text{Online}} | A_{it}] - E[U_{ipt}^{\text{Physical}}] \geq 0
\end{align*}
\]

\[
E[U_{ipt}^{\text{Online}} | A_{it}] - E[U_{ipt}^{\text{Physical}}] \\
= \eta(1 - \delta_{p})E[q_{ipt}] + \theta_{it}(\text{Exp}_{it}, B_{it}, j, t, u_{it})\delta_{p}E[q_{ipt}] - E[q_{ipt}] + price_{p}^{\text{Physical}} - price_{p}^{\text{Online}} \\
= (\eta(1 - \delta_{p}) - 1)E[q_{ipt}] + \theta_{it}(\text{Exp}_{it}, B_{it}, j, t, u_{it})\eta\delta_{p}E[q_{ipt}] + (price_{p}^{\text{Physical}} - price_{p}^{\text{Online}}) \geq 0
\] (3-1)

Suppose that a consumer considers a conventional store and the ISM with \( \eta = 1 \), which means a very well-branded retailer like our research site, and their prices are identical (\( price_{p}^{\text{Physical}} = price_{p}^{\text{Online}} \)), the pivotal formula for channel choice decision is:

\[
\delta_{p}E[q_{ipt}]\left(\theta_{it}(\text{Exp}_{it}, B_{it}, j, t, u_{it}) - 1\right)
\] (4)

### 3.1. Product-level uncertainty reduction (of online shopping experience)

We can reduce equation (2) into equation (5) by expressing \( \delta_{p}E[q_{ipt}]\left(1 - \theta_{it}(\text{Exp}_{it}, B_{it}, j, t, u_{it})\right) \) in \( E[U_{ipt}^{\text{Online}} | A_{it}] \) as one aggregated term of \( \varepsilon_{ipt} \), which measures the decrement of the expected utility due to product-level uncertainty. \(^{32}\)

\[
E[U_{ipt}^{\text{Online}}] = E[q_{ipt}] - price_{ipt} - \varepsilon_{ipt}
\] (5)

While \( \varepsilon_{ipt} \) is zero in offline shopping, it is equal to or greater than zero depending on the product attribute \( \delta_{p} \) multiplied by \( \theta_{it} \) in the online market. For example, when \( \theta_{it} \) is less than 1, the \( \varepsilon_{ipt} \) of clothing is bigger than that of books because consumers can get wider (almost all) information regarding books while they cannot try jeans online. Even though \( \varepsilon_{ipt} \) indicates the uncertainty regarding expected quality of a product, \( \varepsilon_{ipt} \) is not related to the inherent quality (\( q_{ipt} \)), but affected by consumers’ tolerance, \( \theta_{it} \).

\(^{32}\) We assume that (1) consumers shop “inexperienced” goods, which will be discussed in the discussion section.
First, we hypothesize that \( \text{Expit} \) will lead “higher consumer tolerance” (or equivalently, the change from risk aversion to risk lover), by reducing a perceived impact of \( \varepsilon_{\text{qpt}} \) under the fixed \( \delta_p \) of each product. The hypothesis of the product-level uncertainty reduction is rationalized based on two theoretical backgrounds. First, consumers come to take the uncertainty for granted, by adapting themselves to the online purchase environment as they increase online shopping experience (Hobfoll 2002). Consumers frequently choose the option of online shopping that are satisfactory but would be suboptimal if decision costs were zero (Häubl and Trifts 2000) – it is bounded rationality conditional on the available options (Simon 1955) –. This is particularly common when the alternative (here, offline shopping) requires a relatively huge search cost. As a result, consumers can evolve into product-level uncertainty-takers as they increase online shopping experience, willingly embracing the uncertainty. Second, in online shopping, there is a tradeoff between low purchasing cost (searching cost or visiting cost) and low accuracy of expected quality. The satisfaction (or realization) with the benefit of online shopping, which is perceived through (successful) online shopping experiences, can reduce the impact of \( \varepsilon_{\text{qpt}} \) with the weakness of online shopping being outset with or suppressed by the benefit that the consumer may enjoy – finally, increasing consumer tolerance.

The hypothesized change of consumer shopping behavior is derived from comparative statics (or sensitivity analysis) at a critical point (Varian 1992) on equation 4. \( \delta_p E[q_{\text{qpt}}](\theta_{\text{a}}(\text{Expit}, B_{\text{it}}, j, t, u_{\text{it}}) - 1) = 0 \) is by definition the indifferent polyhedron between online and offline shopping. The differentiation of \( \delta_p E[q_{\text{qpt}}](\theta_{\text{a}}(\text{Expit}, B_{\text{it}}, j, t, u_{\text{it}}) - 1) = 0 \) with respect to \( \text{Expit} \) is:

\[
E[q_{\text{qpt}}] \left( \frac{\partial \delta_p}{\partial \text{Expit}} (\theta_{\text{a}}(\text{Expit}, B_{\text{it}}, j, t, u_{\text{it}}) - 1) + \delta_p \frac{\partial \theta_{\text{a}}}{\partial \text{Expit}} \right) = 0 
\]

Because as we described, \( \partial \theta_{\text{a}}/\partial \text{Expit} \) is positive, we can derive the following conditions:

\[
\left( \frac{\partial \delta_p}{\partial \text{Expit}} \right) = \frac{\delta_p}{1 - \theta_{\text{a}}(\text{Expit}, B_{\text{it}}, j, t, u_{\text{it}}) \frac{\partial \theta_{\text{a}}}{\partial \text{Expit}}} > 0 
\]
Equation 7 indicates the expansion of the product spectrum toward the products with more intangible attributes (the diversification of a product spectrum from low $\epsilon_{ipt}$ to high $\epsilon_{ipt}$). Given that, we hypothesize: *As consumers increase online purchasing experience, they are more likely to purchase more intangibility products, supporting the reduction of product-level uncertainty.*

Another hypothesized change related to the reduction of product-level uncertainty is the increase of online transactions in a unit of time. The increment of transactions will render online shoppers to tolerate higher product-level uncertainty because total product-level uncertainty charged to consumers ($\sum_{p=1}^{N} \epsilon_{ipt}$, where $\epsilon_{ipt} \geq 0$) increases as $N$ increase. We will test the hypothesis: *As consumers increase online purchasing experience, they increase the number of transaction in a unit of time.*

### 3.2. How to mitigate product-level uncertainty

Our baseline framework regarding product-level uncertainty reduction is based on individual shopping experience, which is out of the retailers’ direct control although they may induce more transactions with the marketing mix such as discount coupons or intensive customer relationship management (CRM). Instead, online retailers have been trying to adopt mainly two unique “intervention” strategies designed to help convince consumers of the expected quality of products.

#### 3.2.1. Established offline retailer’s reputation transfer

The booming online market has motivated many established offline retailers to newly launch online businesses and their dot.com retailers take advantage of the established offline retailers’ reputation to overcome the weakness of virtual agents. But, the impact of reputation transfer (the value of brand equity) has not been explicated by previous research.

The effectiveness of reputation transfer in reducing product-level uncertainty is inferred based on (1) “indirect experience of products” or (2) “social learning from others’ experiences” that are clarified in previous studies. When consumers try to acquire the information of a product, consumers can experience
the product (1) with physical or actual trials (direct experience), (2) through secondhand source information such as advertising or labels (indirect experience), or (3) with virtual representations of products (virtual experience) (Biocca 1997; Li et al. 2003). In a similar vein, the theoretical models of consumer learning of a product distinguish between learning from one’s own experiences and “social” learning from others’ experiences (McFadden and Train 1996). Here, consumer learning refers to any process that changes a consumer’s memory and behavior as a result of information processing (Arnould et al. 2001; Lavidge and Steiner 1961). In the presence of social learning, consumers delay experimentation until they learn from others that the product is likely to be a good match for them (Clay et al. 2004). In our research context, the value of reputation transfer can be re-clarified into assessment of (1) the value of indirect experience through retailers’ reputation and (2) the good reputation expected to lead to positive social learning. Aiming to assess the impact of the reputation transfer on mitigating product-level uncertainty, we hypothesize: As online retailers utilize offline-established retailers’ reputation, they will induce consumers’ purchase of more intangible products.

3.2.2. The value of digitized video commercials

A “more vivid” demonstration of products is the straightforward way to compensate the omission of experiential information and thus reduce product-level uncertainty. In this line of thought, the demonstration of products along with either (1) “virtual reality (VR) technology” or (2) “digitized videos showing practical trials of show hosts/models with products” is used.

VR interfaces provide high-quality three-dimensional images of products on computer monitor display, alleviating the major constraints caused by the lack of contact between consumers and products online (Klein 2003). VR technology increases high media richness and interactivity as well as make consumers perceive telepresence (Biocca 1997; Klein 2003). As a result, human beings can be highly engaged in a mediated environment, based upon sensory stimuli conveyed by a more vivid demonstration.

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33 Here, the definition of telepresence is a sense of “being there” in an environment by means of a communication medium (Steuer 1992; Reeves and Nass 1996).
In a recent study, Suh and Lee (2005) show via a laboratory experiment that VR interfaces increase overall consumer understanding about products. And they found that the effects of VR extend to virtually-high-experiential (VHE) products more significantly than to virtually-low-experiential (VLE) products, where the classification is based on the sensory modalities that are used and required for product inspection.\footnote{One can map an intangible attribute (a tangible attribute) into VHE (VLE) without reasoning gap.} Actually, previous studies investigated relatively closely the impact of VR, whereas the impact of digitized commercial video has not been fully explored. Video commercials were introduced more recently than VR technology to the online market because of its high cost and also it demands much a bigger bandwidth than VR.\footnote{The digitized videos have become more and more popular as consumers are able to access high-speed internet service because it requires greater bandwidth. According to Korean telecom’s report, broadband service has been provided in Korea since 1998. The starting point of our data is January 2002, when broadband Internet service was diffused enough.} Nowadays, some ISMs are manufacturing commercial videos by themselves or using (digitizing) commercial videos developed for other retailing channels such as home shopping (HS). Compared to VR technology, the commercial video may be more vivid and persuasive even if there is no interactivity. Given that, we hypothesize: \textit{When online retailers provide product information with digitized commercial video in addition to typical text and image, they can induce consumers’ purchase of more intangible products.}

The two hypotheses associated with ISMs’ intervention strategies are congruent with the equation
\[
\left(\delta_p / \delta j\right) = \left(\delta_p / \left(1 - \theta \right)\right) \left(\delta \theta / \delta j\right) > 0
\]
derived in the similar manner to equation 7. The unique structure of three information methods shown in our research site enables us to test both hypotheses. If those hypotheses are verified, we subsequently aim to answer \textit{“how effectively does the utilization of reputation (or digitized video commercials) work, compared to other sources to mitigate product-level uncertainty?”}

3.3. The change of price spectrum of products purchased online

In this section, we turn our concern to the change of the price spectrum of products purchased online, which may give us substantial insight regarding online shopping behavior on the account that consumers’ reservation price setting in an intangible (non-digital) attribute portion is still uncertain – even
though consumers may fix the reservation price in a tangible attribute portion. To analyze the change of the product price spectrum, we set the unit of analysis as a market basket composed of multiple items purchased in a unit of time. Suppose that a consumer purchases \( N \) multiple items in a unit of time, we develop two metrics: (1) average price and (2) highest price, both of whose variations enable us to capture the dynamic change of product price spectrum as well as infer, on average, the influence of a product price on consumers’ channel choice of online vs. offline.

All other things being equal (in particular, a product attribute), one expects that individual online shopping experience induces the increase of both measures through the product-level uncertainty reduction process – the hypothesized increase of \( \theta_i \) and \( B_i \). But, as an opposite force, online consumers are reluctant to purchase relatively expensive products without physical cue because the more expensive the product is, the more risky it is, regardless of increment of online shopping experience. Given these competing forces, the dynamic changes of price-related measures (equivalently, the product price spectrum) cannot be clearly determined. Instead, we build all possible scenarios for potential outcomes on the two dimensions, which are summarized along with the practical grounds in Table 4. We will examine which one is correct given the hypothesized 7 scenarios.

<table>
<thead>
<tr>
<th>Increase of average price</th>
<th>No change of average price</th>
<th>Decrease of average price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase of highest price</td>
<td>Extension of product spectrum toward expensive items</td>
<td>No change of highest price</td>
</tr>
<tr>
<td>No change of highest price</td>
<td>Extension of product spectrum toward both ways</td>
<td>No extension of product spectrum</td>
</tr>
<tr>
<td>Decrease of highest price</td>
<td>Extension of product spectrum toward both ways (weakly expensive and strongly cheap items)</td>
<td>Extension of product spectrum toward cheap items</td>
</tr>
</tbody>
</table>

Table 4.2. The hypothesized scenarios in change of product price spectrum

4. Model Specification

4.1. Product-level uncertainty reduction model 1 (individual shopping experience)

The estimation framework is based on a regression, which is meant to capture the causal effect of potential explanatory variables on product-level uncertainty. For the \( i \)th consumer at time \( t \), we assume
that product-level uncertainty is given by:

\[ y_t = \alpha_1 \text{Exp}_{t-1} + \alpha_2 t + \mathbf{z}' \mathbf{\beta} + \omega_j + u_t \]  

\( y_t \) is one of four measures developed to measure a product-level uncertainty level:

1. \( AIL_{it} = \sum_{p=1}^{N} I_{ip} / N \),
2. \( N_{it} \): number of purchased products in time \( t \)
3. \( \text{APrice}_{it} = \sum_{p=1}^{N} \text{Price}_{ip} / N \),
4. \( \text{HPrice}_{it} = \max[\text{Price}_{i1t}, \text{Price}_{i2t}, \ldots, \text{Price}_{iNt}] \)

The measures are calculated based on a market basket of products individual consumers purchase in a unit of time \( t \) (not one shopping trip). Unlike the other three uncertainty measures, average intangibility level (\( AIL_{it} \)) requires the prerequisite assignment of an intangibility level (\( IL_p \)) on every product. To calibrate \( IL_p \), as the first step, we set 2333 product categories (\( Category_p \)) with four layers of product classification criteria that category managers use.\(^{36}\) Second, we assign intangibility levels – 1: most tangible (e.g., book), 2: less tangible (e.g., wireless router), 3: moderate tangible (e.g., bicycle), 4: less intangible (e.g., earring), 5: most intangible (clothing) on a five-point Likert-scale (see the online appendix) – on every category. Then we discussed the assignment of intangible level of categories with people of diverse ages and both genders and incorporate their opinions. Third, if each product is classified into one among 2333 categories, its intangibility level is automatically determined.

The regressor of main interest, \( \text{Exp}_{it-1} \) is the total cumulative number of online transactions through \( t-1 \), which is added to capture the transition of state associated with product-level uncertainty reduction. Another term, \( t \) is for capturing a time-variant transition such as technology advancement and/or social trend – as shown in subscript of equation (8), we assume that \( t \) is common to all consumers. \( \mathbf{z}' \mathbf{\beta} \) is consumer heterogeneity (or individual effect), where \( \mathbf{z}_i \) contains a constant term and a set of individual specific variables (age and sex). Our baseline model is a random effect model, where the informative methods, \( \omega_j \) is not fixed unknown constants, but are assumed to be independent random

\(^{36}\) It is composed of large, medium, small, and tiny classifications. The classification of Hmall-procured products is more closely accessible. But the product classification applied to the other two channels is close enough to assign intangibility levels.
variables. That is, we assume that consumers purchase items across all categories ($Category_p$) at any time $t$, and the most attractive item is found randomly across channels ($j$).\(^{37}\) The error component, $u_{it}$ is idiosyncratic errors and it changes across $t$ as well as across $i$.

### 4.2. Product-level uncertainty reduction model 2 (ISMs’ strategy)

In this section, our primary goal is to examine whether product-level uncertainty is affected by information that consumers are able to acquire when they make a purchasing decision of a product – i.e., to assess the value of new informative methods, which are ISMs’ intervention strategies.\(^{38}\) The regression models are obtained from the preceding one by including additional informative method dummy variables – indicating different sets of information given to online consumers – on intercept (informative method specific intercept) in equation (9), and both intercept and slope coefficients (informative method specific transition) in equation (9-1).

\[
y_{it} = \sum_{s>0} \alpha_{0s} D_s + \alpha_1 \exp_{it-1} + \alpha_2 t + z_i' \beta + u_{it} \tag{9}
\]

\[
y_{it} = \sum_{s>0} \alpha_{0s} D_s + \sum_{k=0} \alpha_{1k} D_k \exp_{it-1} + \alpha_2 t + z_i' \beta + u_{it} \tag{9-1}
\]

\[
D_j : D_0 = \text{ISM}, D_1 = \text{ISM_DS}, \text{& } D_2 = \text{ISM_HS}
\]

The ideal evaluation strategy for two different intervention strategies: (1) reputation transfer and (2) vivid demonstration with digitized video commercial would involve the random assignment of both consumers and products to three informative methods. Random assignments insure that both consumers and products across all informative methods are indeed comparable, so that any difference in uncertainty reduction transition could be confidently attributed to the characteristics of informative methods. While the assumption associated with the random assignment of products across informative methods is practically supported – as we described in the research site section –, we cannot confirm the random assignment of consumers across informative methods. The violation of the random assignment may cause a selectivity bias problem. That is, the difference in uncertainty reduction process across informative

\(^{37}\) $\text{Cov}(Exp_{it-1}, \omega_i) = \text{Cov}(t, \omega_i) = \text{Cov}(z_i, \omega_i) = 0$.

\(^{38}\) Here, we assume that the effect of ISMs’ interventions (or any difference across informative methods) is fixed over time.
methods may be because people who buy intangible products prefer DS-procured products or because each person chooses to buy their intangible products from DS-procured products and their tangible products from HS-procured products. Assuming that the individual propensities regarding channel selection is captured by $z_i$ in equation 9 and 9-1, the variation of uncertainty measures across informative methods might be attributed to channel characteristics. Further, we estimate the model based on an individual consumer fixed effect model releasing the assumption – using $\tau_i$ (individual effect) instead of $z_i \beta$.

5. Data and Empirical Results

The main data for this study is the transaction data of a random sample of consumers who shopped at our research site from January 2002 to June 2006 (around 4 and half years). The data show the total number of transactions as 1,389,449 and the total number of consumers as 172,175, indicating one customer shopped on average 7.93 times during the research period. We can get the information associated with (1) individual demographics (age and gender) on each transaction and (2) product attributes (category, price, suppliers, and transaction date) on each transaction and (3) product category classification codes provided by category managers. Descriptive statistics is reported in Table 3 on every combination of informative methods and price ranges (or individual demographic factors).

<table>
<thead>
<tr>
<th>Price_Range</th>
<th>ISM (1)</th>
<th>ISM_DS (2)</th>
<th>ISM_HS(3)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td># of transactions</td>
<td>947,289</td>
<td>206,574</td>
<td>235,586</td>
<td>1,389,449</td>
</tr>
<tr>
<td>[0,$10)</td>
<td>76,189</td>
<td>978</td>
<td>142</td>
<td>77,309 (0.055)</td>
</tr>
<tr>
<td>[$10,$50)</td>
<td>440,206</td>
<td>93,988</td>
<td>25,651</td>
<td>559,845 (0.402)</td>
</tr>
<tr>
<td>[$50,$150)</td>
<td>314,366</td>
<td>94,713</td>
<td>139,617</td>
<td>548,696 (0.394)</td>
</tr>
<tr>
<td>[$150,~)</td>
<td>116,528</td>
<td>16,895</td>
<td>70,176</td>
<td>203,599 (0.146)</td>
</tr>
<tr>
<td>AIL</td>
<td>2.61</td>
<td>3.65</td>
<td>3.10</td>
<td></td>
</tr>
<tr>
<td>[0,$10)</td>
<td>2.57</td>
<td>3.26</td>
<td>1.01</td>
<td></td>
</tr>
<tr>
<td>[$10,$50)</td>
<td>2.73</td>
<td>3.56</td>
<td>2.294</td>
<td></td>
</tr>
<tr>
<td>[$50,$150)</td>
<td>2.53</td>
<td>3.73</td>
<td>3.35</td>
<td></td>
</tr>
<tr>
<td>[$150,~)</td>
<td>2.37</td>
<td>3.74</td>
<td>2.90</td>
<td></td>
</tr>
<tr>
<td>Average Price ($)</td>
<td>98.39</td>
<td>71.005</td>
<td>181.007</td>
<td></td>
</tr>
<tr>
<td>[0,$10)</td>
<td>7.08</td>
<td>7.34</td>
<td>9.55</td>
<td></td>
</tr>
</tbody>
</table>

We found that address and occupation are incomplete so that we cannot use their information for statistical analysis.
Table 4.3. Descriptive statistics

Table 3 shows that HS-procured products ($181) are on average more expensive than both Hmall-procured ($98.4) and DS-procured products ($71.0) – this is consistent to information acquired from interview with category managers regarding product selection procedure –, causing product price heterogeneity across the informative methods. To control them, we split the whole sample into four groups based on the price range.

AIL ranges from 2.61 to 3.65 according to informative method when we don’t consider price range. It is comparative evidence of differences in AIL across the informative methods (AILISM_DS > AILISM_HS > AILISM). But, this difference would result from the heterogeneity of intangibility levels of products sold across informative methods – as we described in the research site, a product is not sold in multiple channels. Therefore, we examine product category heterogeneity instead of product heterogeneity across informative methods – product category heterogeneity is expected to allow us to control the product heterogeneity across informative methods on the account of such a detail classification of product categories (2333 product categories). The best way to control product category heterogeneity is to examine all categories calibrated based on all the products displayed on the web, regardless of purchasing event (occurrence) of the products. We, however, could not get the information due to lack of associated record and long research period. As an alternative method to control product category heterogeneity, we examined the product categories in which at least one transaction occurred. Further, we investigated whether a certain category occupies the majority of transactions on every price range across informative methods. Transactions involved in first price range, [0,$10), share 5.5% of all transactions. 98.5% of all transactions in the first price range happened in Hmall-procured products, and transactions did not happen in many product categories of the other two channels, indicating the severe heterogeneity.
of product category spectrum across informative methods in the price range. It seems that there is no severe product heterogeneity in the second price range. But there were no transactions in several categories of HS-procured products and a considerable portion of all transactions are occupied by only a few categories.\textsuperscript{40} We confirmed that there is no product category heterogeneity across informative methods in other samples except for the three samples (among 12 samples divided based on both price range and informative methods) – refer to the online appendix for the details of product heterogeneity.

5.1. Average intangibility level (AIL)

We, first, estimated the product-level uncertainty reduction model as measured by $AIL_{it}$, where the unit of observation (dependent variable) is $AIL_{it}$ calculated from consumer $i$’s market basket at time $t$ – a unit of time is 6 months --, and explanatory variables are shown in the first column of Table 4.

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online shopping experience</td>
<td>0.0022***</td>
<td>0.0012***</td>
<td>0.0012***</td>
</tr>
<tr>
<td></td>
<td>(40.36)</td>
<td>(22.69)</td>
<td>(13.16)</td>
</tr>
<tr>
<td>ISM_DS Dummy</td>
<td>0.789***</td>
<td>0.796***</td>
<td>0.796***</td>
</tr>
<tr>
<td></td>
<td>(200.18)</td>
<td>(176.70)</td>
<td>(176.70)</td>
</tr>
<tr>
<td>ISM_HS Dummy</td>
<td>0.352***</td>
<td>0.377***</td>
<td>0.377***</td>
</tr>
<tr>
<td></td>
<td>(108.59)</td>
<td>(104.70)</td>
<td>(104.70)</td>
</tr>
<tr>
<td>ISM Dummy* Online shopping experience</td>
<td>0.0019***</td>
<td>0.0012***</td>
<td>0.0012***</td>
</tr>
<tr>
<td></td>
<td>(24.74)</td>
<td>(13.16)</td>
<td>(13.16)</td>
</tr>
<tr>
<td>ISM_DS Dummy* Online shopping</td>
<td>0.00004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>experience</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ISM_HS Dummy* Online shopping</td>
<td></td>
<td></td>
<td>0.00004</td>
</tr>
<tr>
<td>experience</td>
<td></td>
<td></td>
<td>(0.47)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0022***</td>
<td>-0.0017***</td>
<td>-0.0018***</td>
</tr>
<tr>
<td></td>
<td>(-12.82)</td>
<td>(-10.70)</td>
<td>(-10.77)</td>
</tr>
<tr>
<td>Gender</td>
<td>-0.443***</td>
<td>-0.373***</td>
<td>-0.372***</td>
</tr>
<tr>
<td></td>
<td>(-218.56)</td>
<td>(-187.83)</td>
<td>(-186.54)</td>
</tr>
<tr>
<td>Period (Calendar time)</td>
<td>0.020***</td>
<td>0.0078***</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(37.48)</td>
<td>(14.54)</td>
<td>(13.80)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.941***</td>
<td>2.777***</td>
<td>2.76***</td>
</tr>
<tr>
<td></td>
<td>(455.75)</td>
<td>(442.64)</td>
<td>(440.52)</td>
</tr>
<tr>
<td>N</td>
<td>580.377</td>
<td>580.377</td>
<td>580.377</td>
</tr>
<tr>
<td>R-square</td>
<td>0.09</td>
<td>0.16</td>
<td>0.15</td>
</tr>
<tr>
<td>R-square</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\textit{t}-statistics are shown in parentheses

*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$(Based on robust standard errors)

Table 4.4. Estimated Results (AIL)

\textsuperscript{40} We cannot describe the detail information according to the data provider’s request.
The results for model 1 (based on equation 8 – informative method random effect model –), show that individual online shopping experience significantly induces the growth in $AIL$ – recall that intangibility level ranges from 1 (most tangible) through 5 (most intangible) –, indicating that consumers are likely to purchase more intangible products as they purchase more products online. That is, the results support the decrease of the impact of $e_{ipt}$ in online purchasing decision, which was theorized based on (1) the change of the consumers’ behavior toward product-level-uncertainty-takers and/or (2) consumers’ realization of the online shopping benefit surpassing the product-level uncertainty through online shopping experience.

Using dummy variables (informative method-specific intercepts) and $AIL$ calculated in every informative method, $j$ ($AIL_{ijt}$) – based on equation 9 distinguishing ISM, ISM_DS, and ISM_HS –, we found that both the reputation transfer and the vivid demonstration with digitized commercial video increase the transactions of more intangible products, being able to substitute product-level uncertainty reduction process derived from online shopping experience (see Model 2). While (1) online shopping experience, (2) reputation transfer, and (3) more vivid informative demonstration extend product spectrum toward more intangible products, our results show big difference in their impacts. The impact of reputation transfer is greater than that of ten units more shopping experience by around 70, and the value of reputation transfer is twice more effective than the impact of a commercial video – the utilization of offline established retailer’s brand equity is a stronger intervention strategy than commercial video in inducing purchase of intangible products –. In model 3 (based on the equation 9-1), the interaction terms are positive and significant in both Hmall-procured and DS-procured products while the coefficient of interaction terms of online shopping experience and HS dummy is not statistically significant. Given that, we can infer that online shopping experience is still effective in inducing intangible products in DS-procured products, whose uncertainty is already reduced to some extent through the reputation transfer process, whereas a vivid demonstration through a commercial video can overwhelm the product-level uncertainty process of online shopping experience – i.e., reputation transfer and online shopping experience can make synergy and vivid demonstration and shopping experience cannot.
The results show that female and younger consumers are more likely to try intangible products—it is easily understandable on the account that women and the younger age group are more interested in high intangible products such as clothing and fashion. We found out that there is a time-variant transition (or social trend) inducing the extension of product spectrum toward an intangible product line, being congruent with the expectation. That is, we confirmed the change of online customers’ attitude (social trend or the impact of technology advancement such as better display technology diffusion) favoring online shopping with period dummies. The calendar time is positively correlated with cumulative online shopping experience. We, however, confirmed that there is no severe multicollinearity problem by checking VIF (Variation Inflation Factor).

5.2. AIL and product price

As we mentioned, we confirmed that there is heterogeneity in the distributions of product price across three informative methods. Thus, the comparison of AILs across three informative methods might not be directly comparable without distinguishing the compounding effect of (1) influence of informative methods (of concern) and (2) the impact of distributional heterogeneity of price on the variation of AIL across information methods.

As we mentioned, we found that there is no sufficient product category spectrum across informative methods in three cells: ‘ISM_DS and [0,$10)’, ‘ISM_HS and [0,$10)’, and ‘ISM_HS and [$10, $50)’. Thus, we estimated models with both the product category heterogeneity and product price heterogeneity across informative methods controlled except the above three samples.

In addition to findings from preceding analysis, these results give us an intriguing understanding of a different product-uncertainty reduction process—consumers’ different online shopping behavior—depending on a product price (see Table 5, where the regression results based on individual consumer fixed effect model are reported in a separate column mapping a corresponding price range).41 Online shopping experience can induce the purchase of more intangible items only in the moderate price range of

41 The correlation between AIL and price is -0.05.
[\$50, \$150), whereas the causal relationship is not valid in both the very cheap product line of \([0, \$10)\) and the very expensive line of \([\$150, \sim)\). It is explicable that the product-level uncertainty reduction process is not observed in cheap product items. Online consumers are expected to buy intangible items regardless of the amount of online shopping experience because the maximum (financial) loss inducible from the uncertainty is as much as a product price. However, the uncertainty reduction process doesn’t occur in the purchase of expensive products. One potential explanation is that individual shopping experience cannot overcome product-level uncertainty if the product of interest is an expensive product – i.e., even consumers with relatively many online purchasing experience (heavy online shoppers) are unlikely to purchase expensive products online. Another possible explanation for “no product-level uncertainty reduction process” in the expensive products, is the price signaling effect (Milgrom and Roberts 1986). That is, the high price, itself, can give consumers the signal of high quality so that consumers may buy expensive products even though online shopping experience is small. Given two competing forces, the estimated causal relationship of online shopping experience and highest price (to be shown the next section) shows that the price signaling effect may not be a viable explanation.

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>([0,$10))</th>
<th>([$10,$50))</th>
<th>([$50,$150))</th>
<th>([$150,\sim))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shopping experience</td>
<td>-0.0011***</td>
<td>0.00056***</td>
<td>0.00038**</td>
<td>0.00019**</td>
</tr>
<tr>
<td>ISM_DS Dummy</td>
<td>-</td>
<td>0.322***</td>
<td>0.463***</td>
<td>0.976***</td>
</tr>
<tr>
<td>ISM_HS Dummy</td>
<td>-</td>
<td>-</td>
<td>0.504***</td>
<td>0.292***</td>
</tr>
<tr>
<td>Period (Calendar time)</td>
<td>0.078***</td>
<td>0.0078***</td>
<td>0.003***</td>
<td>0.028***</td>
</tr>
<tr>
<td>Constant</td>
<td>2.78***</td>
<td>3.03***</td>
<td>2.92***</td>
<td>2.70***</td>
</tr>
<tr>
<td>N</td>
<td>37,109</td>
<td>240,309</td>
<td>332,018</td>
<td>141,683</td>
</tr>
</tbody>
</table>

| R-square             | 0.04          | 0.03           | 0.12           | 0.10           |

| t-statistics are shown in parentheses |
| Individual fixed effect analysis |
| *Significant at \(p < 0.05\) **Significant at \(p < 0.01\) ***Significant at \(p < 0.001\) |

Table 4.5. Estimated Results (AIL and product price)

It is noticeable that contrary to individual shopping experience, ISMs’ uncertainty reduction strategies turn out to still be effective in expensive product lines. As shown in third and fourth columns of
Table 5, the estimated coefficients of reputation transfer (ISM_DS) is still bigger than those of vivid demonstration (ISM_HS), which is identical to results shown in Table 4. Furthermore, the difference becomes bigger in expensive product lines. The more expensive the product is, the more effective the strategy of reputation transfer is. This finding provides us insight of how online shoppers handle product-level uncertainty. Online consumers trust the established offline retailers’ reputation around twice more than vividly shown online demonstration. That is, even though online consumers shop in the “online world”, they are inclined to trust the indirect experience (or social learning) associated with the “offline world” (Bandura 1977; McFadden and Train 1996) more than virtual experience available within the “online world”.

5.3. The number of transactions, average price, and highest price.

Table 6 presents the estimates of the number of transactions, average price, and highest price (as a dependent variable, the measures are extracted from a set of products purchased every six months on an individual level – $N_{it}$, $APrice_{it}$ and $HPrice_{it}$).

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th># of transaction</th>
<th>Average Price</th>
<th>Highest Price</th>
<th>Highest Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shopping experience</td>
<td>0.0062***</td>
<td>-414.2***</td>
<td>-411.4961***</td>
<td>-1231.224***</td>
</tr>
<tr>
<td></td>
<td>(964.82)</td>
<td>(-12.54)</td>
<td>(-7.15)</td>
<td>(-21.14)</td>
</tr>
<tr>
<td>The # of purchase</td>
<td>-</td>
<td>-1308.9 ***</td>
<td>-</td>
<td>9579.774***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-16.92)</td>
<td></td>
<td>(70.22)</td>
</tr>
<tr>
<td>Period (Calendar time)</td>
<td>0.022***</td>
<td>1921.88***</td>
<td>810.9436</td>
<td>3248.733***</td>
</tr>
<tr>
<td></td>
<td>(68.20)</td>
<td>(11.41)</td>
<td>(2.73)</td>
<td>(10.94)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.903***</td>
<td>122988.7****</td>
<td>180451.5****</td>
<td>151951****</td>
</tr>
<tr>
<td></td>
<td>(612.32)</td>
<td>(193.44)</td>
<td>(171.28)</td>
<td>(135.54)</td>
</tr>
<tr>
<td>N</td>
<td>474159</td>
<td>474159</td>
<td>474159</td>
<td>474159</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-1284184.3</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Pseudo (R-square)</td>
<td>0.11</td>
<td>0.09</td>
<td>0.017</td>
<td>0.028</td>
</tr>
</tbody>
</table>

$t$-statistics are shown in parentheses, $^*$ Zero Inflated Poisson regression

The analysis is based on Korean currency (won). $1$ is roughly equivalent to ₩1000

Individual fixed effect analysis

*Significant at $p < 0.05$ **Significant at $p < 0.01$ ***Significant at $p < 0.001$

We found that (1) the number of individual consumer’s transactions in a unit of time is positively affected by $Exp_{i,t-1}$ (0.0062, $t$-statistics = 964.82), (2) the impact of $Exp_{i,t-1}$ on average price is negative and
significant (-$0.41, \( t \)-statistics = -12.54), and (3) the impact of \( Exp_{it-1} \) on highest price is negative and significant irrespective of whether \( N_{it} \) is not included as a covariate in the model.

Here, we have to be very cautious of the causal interpretation of the result regarding highest price, because the highest price in a market basket is expected to be correlated with the size of the basket (equivalently, the number of transactions in the time unit). We have to include \( N_{it} \) in the regression model in order to avoid an omitted variable problem, which might generate spurious estimate of online shopping experience. Actually, we confirmed the positive relationship of \( N_{it} \) and \( HPrice_{it} \) in the correlation matrix as well as from the sharp change of \( Exp_{it-1} \) coefficient from column 4 to column 5. That is, a relatively small negative coefficient shown in the fourth column of the Table 6 can be attributed to the indirect effect (or the mediating effect) of \( N_{it} \). We confirmed that \( N_{it} \) plays a mediating role of the relationship between online shopping experience and highest price, following the steps for mediation testing presented by Baron and Kenny (1986). In calculating the indirect effect of online shopping experience on the highest price, the impact turns out to be $0.59, which indicates the overestimation of the impact of online shopping experience on highest price due to an omitted variable (-$0.41).\(^{42}\) Including indirect effect of online shopping experience through the number of transactions on highest price, one more unit of online shopping experience decreases the highest price by $0.63 – that is, \( Exp_{it-1} \) cannot directly induce the purchase of more expensive products. This suggests the possibility that the product-level uncertainty prevents online consumers from purchasing expensive products because online consumers are reluctant to purchase relatively expensive products without physical cue –. And, online shopping experience does lower the average price. The findings, when considered together, show that the price spectrum of products purchased on an individual level changes and that the direction of transition is heading only cheaper product lines – as a matter of fact, both findings are counter-intuitive. We asked the expected influence of online shopping experience on highest price and average price to at least 20 people on campus. All of them answered that it would be positive. Here, confirming that the product price spectrum moves into

\(^{42}\) Alternatively, we examined the impact of \( Exp_{it-1} \) on highest price when we hold the number of transactions at a certain fixed number. The coefficient of \( Exp_{it-1} \) is not significant when holding the number of transaction as 3 transactions and it is negative and significant in the case of holding 5 transactions. The coefficients are negative regardless of the fixed number of transactions.
cheaper product lines, we are left with an interesting question of “why consumers do not buy a cheaper product when they are in the early stage of online shopping history (when their online shopping experience is very small)?” The most viable explanation of the result is the impact of shipping and handling charges on consumer purchasing behavior. Consumers are very sensitive to shipping charges and shipping fees influence order incidence (Lewis et al. 2006; Rosen and Howard 2000). So, the products of “modest” price range would be more appealing to online shoppers than the products with a relatively big portion of shipping fees when they first start considering online purchasing.

As a result, the scenario of “decrease of both highest price and average price” is empirically supported among our hypothesized scenarios concerning the change of the product price spectrum induced from online shopping experience.

<table>
<thead>
<tr>
<th>Increase of Highest price</th>
<th>No change of Highest price</th>
<th>Decrease of Highest price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase of average price</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>No change of average price</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Decrease of average price</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Table 4.7. The change of the product price spectrum induced from online shopping experience

6. Discussion and conclusion

This study is motivated by an idea that product-level uncertainty is embedded in online shopping – which has not been empirically explored – in addition to virtual retailer-relating uncertainty that has received much attention. Developing four measures to capture the product-level uncertainty based on an individual market basket, we theorized both (1) their longitudinal variation and (2) their variation across informative methods, and estimated the corresponding product-level uncertainty reduction models. In particular, the transition of the product spectrum in two dimensions of (1) the intangibility level (defined in this study) and (2) the price spectrum of purchased products may widen our understanding of consumer purchasing behavior in the online environment as well as be applied to the ISMs’ short or long-term strategic planning. In the next section, we consider the viability of some alternative explanations for these findings.
6.1. Robustness checks

Here, we articulate unobservable factors that might be able to affect our findings, but were not (fully) designated in our model specification: (1) the variation of product price during the research period, (2) the increase of “repurchased” goods, (3) external competitors outside our research site and systematic product price dispersion, (4) the purchase of returnable items, and (5) lenient return policy.

The potential alternative explanation of the results associated with the change of average and highest price should be the systematic variation of product prices during our research period. Since the product spectrum of consideration covers almost all product categories, we examined consumer price indexes (CPI). According to a Korean governmental report, CPI increased by on average 3 or 4% in our research period (2002~2005: 106.8, 110.7, 114.7, 117.8). Our finding is that two price-relevant measures are negatively affected by $Exp_t$ and calendar time $t$. Because of the upward trend of CPI, the negative impact of $Exp_t$ might be underestimated and cannot be overestimated. Therefore, our findings of “decrease of both highest price and average price” are robust.

The most straightforward alternative explanation in product-level uncertainty reduction process in AIL will be the increase of “repurchased” goods. The product-level uncertainty is zero in the repurchasing decision so that the expansion of product spectrum toward intangible product lines might result from the increase of repurchased products with high intangible attributes, not from the product-level uncertainty reduction process. Analyzing the model with the sample excluding multiple purchased products both at the same period and at different periods, we confirmed that the increase of “repurchased” goods is not a viable explanation in the uncertainty reduction model.

Since the data comes from one of the ISMs in a local market, the external factors from rival ISMs may systematically affect the consumers’ purchasing behavior at our research site. In particular, price dispersion across rival ISMs with a similar level of retailer-brand awareness could be a substantial omitted variable affecting our results. The data regarding price dispersion is not available. However, the interview with the category managers (who are price setters in the context) shows very interesting
situations and evidence that the substantial price dispersion across competing ISM’s does not exit. Category managers check daily the price dispersion and try to benefit from the price edge, showing Bertrand competition among big ISMs in the Korean online market. In contrast to the Bertrand explanation, Campbell et al. (2005) suggests the possibility of the collusion with monitoring in the online market. If the same technology that eases consumer search also allows firms to monitor each other’s prices more easily, then firms can more easily detect cheating on a collusive price arrangement. We observed that category managers gaze steadily at competitor price and don’t overlook disadvantage in the price competition. Given that, we don’t evaluate which model is more appropriate in describing the Korean online market structure involving our research site. But, neither Bertrand nor Campbell’s equilibrium will weaken our findings in that prices of the same product available on rival ISMs are supposed to converge to a relatively similar price to some extent. Similarly, even though the measure of $Exp_i$ was calculated based on only one ISM, the measurement can be representative of individual online shopping experience – the accumulation of online shopping experience on a certain ISM is proportionate to that from whole ISM’s – because there is not a systematic price dispersion across rival competitors and even if there is, it is negligibly slight and a random walk at a certain time.

The data we collected contains only the transactions completed without returning and we cannot observe consumers’ return experience. Consumers can return new, unopened items sold within 30 days of delivery for a full refund and the basic policy corresponds to all informative channels. The cost of returning a product is generally attributed to consumers if the returning cause is on the consumer side. And the research site manages black list of consumers returning frequently and restricts their purchases. Considering all of them, we may assume that the data show consumers’ rational purchasing decisions rather than moral hazard behavior.

Lenient return policy decreases deliberation time for purchasing decision (Wood 2001) and so one would infer that returnable products reduce the impact of product-level uncertainty in purchase

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43 Bertrand competition may be supported by (1) homogeneous products (homogenous product lines), (2) the same marginal cost (easily assumed), and (3) practical assumption that consumers buy everything from the cheaper retailer under the same retailer brand awareness.
decision. Therefore, our estimated coefficients of $Exp_{it}$ and two intervention effects could be underestimated, but overestimation of the coefficients are very highly unlikely. Given that, the fact that consumers can return a product after physically checking the product quality (or the purchase of returnable products) don’t fade our findings associated with impact of product-level uncertainty.

### 6.2. Limitation and future research direction

In attempting to build an analytical framework and quantify the measures, some restrictive assumptions are required. We assume that $\epsilon_{ipt}$ occurs due to the omission of physical investigation. But there are some potential factors hedging the product-level uncertainty but being not related to physical investigation. The failure of fully controlling those factors will be an obvious limitation of the current study. One of them could be product-brand awareness. If consumers don’t have prior experience with a certain product, a halo effect may exist (Asch 1946). That is, product brand awareness can compensate the level of uncertainty of Internet-based intangible attributes (Alba et al. 1997; Danaher et al. 2003; Nelson 1974). For specific examples, branding and detailed product specifications act to transform a product from an experience good into a search good (Nelson 1970). Larger brands are therefore capable of providing sufficient information for consumers to predict satisfaction without experiencing the merchandise (Alba et al. 1997). Future research should attempt to extend our findings by explicitly incorporating the effect of product-brand awareness.

Our model captures consumer heterogeneity with their demographic profile (with individual effect model). But there could be other unobservable constructs elaborately capturing consumer heterogeneity. One potential measure will be consumer shopping behavior such as ‘heavy shopper’ vs. ‘light shopper’. We tried to measure the shopping behavior (‘heavy shopper’ vs. ‘light shopper’) based on the number of individual transactions in a unit of time. The metrics are very restricted due to the multicollinearity problem in the regression model. The different shopping behaviors may or may not be observed depending on groups segmented based on shopping behavior. This could be a very interesting future research topic.
Additionally, a more sophisticated model could also reflect both (1) purchasing frequency in product categories and (2) the different purchasing rates of different categories, like the Dirichlet model (Goodhardt et al. 1984). The systematic variation between the distribution of durable and non-durable goods and our metrics could exist and the relationship could extend our understanding of product-level uncertainty reduction process. These questions could be an interesting research direction in the near future.

Although the product-level uncertainty reduction process is consistent with our predictions, the process is attributed to consumers’ learning progress in determination of the fit or feel of intangible products online. So, consumers can better estimate the mean of the intangible attributes as well as reduce its variance with online shopping experience.
Chapter 5: Trajectory-based Consumer Segmentation and Product Positioning in the Online Markets

Abstract

The dynamic change of online purchasing behavior has received much attention from both managers and academicians (Bellman et al. 1999; Lohse et al. 2000). In this study, we aim to understand the distinctive longitudinal shopping pattern and further suggest how to use this better understanding. We, first, identify clusters of individuals following similar progressions of shopping behavior on three dimensions: (1) product intangibility – a measure of the difficulty encountered by an online consumer in assessing the fit between his/her requirements and the features of a product (Degeratu et al. 2000; Lal and Sarvary 1999; McCabe and Nowlis 2003) –, (2) product price, and (3) the number of transactions in unit time. The data source for this study is an individual-level transaction data of the random sample of customers shopping at our research site from January 2002 to June 2006. We found the following distinctive patterns of online shopping behavior based on trajectory-based segmented groups: (1) consumers showing high purchasing frequency in unit time are likely to increase the purchasing frequency over time, while consumers purchasing with relatively low purchasing frequency show constant purchasing frequency over time, (2) consumers purchasing (relatively) more intangible items tend to expand the mix of products toward more intangible products over time while consumers purchasing mainly tangible items limit themselves to highly tangible products even if they increase their online shopping experience over time and (3) online shoppers purchasing relatively inexpensive products continue purchasing products in this price range while consumers purchasing relatively expensive products are likely to purchase more expensive products over time. We find interestingly that estimated trajectories do not overlap at any time in all three behaviors. Second, using a Bayesian approach, we develop the framework of how to use knowledge of the trajectory groups to develop an optimal product positioning approach that predicts the probability that a good with a particular set of attributes – price and intangibility level – will be purchased by a member of the trajectory group. This product positioning strategy can be used in targeted email campaigns as well as in dynamically generating content to be shown to customers on web pages. We conclude with a discussion of the managerial implications of our research.

Keywords: Online Purchasing Pattern; Product-Level Uncertainty; Trajectory Analysis; Segmentation; Consumer heterogeneity; One-to-one Marketing; Customer Relationship Management (CRM)
1. Introduction

Since online retailing has gradually occupied more and more of the retailing business, online purchasing behavior has received much attention from both managers and academic scholars. Most of the previous work lists substantial elements and examine their influence based on cross-sectional data (Bakos 2001; Brown and Goolsbee 2002; Brynjolfsson and Smith 2000; Clay et al. 2002; Clemons et al. 2002; Keeney 1999; Lynch and Ariely 2002; Novak et al. 2000; Smith et al. 2000; Torkzadeh and Dhillon 2002). Even though some studies analyze the dynamic online purchasing pattern based on panel data in the online market (Bellman et al. 1999; Lohse et al. 2000), they are still focused on searching for and illuminating predictors of online purchasing behavior (e.g., individual demographic profile, marketing mix, either retailer or product brand effect).

Recently, Kim et al. (2007) examines the change of online purchasing behavior over time on an individual level, where consumer heterogeneity is controlled either with consumers’ demographic profiles or through the individual fixed effect model in model specification – if heterogeneity is present but is ignored in the analysis, it should result in biased and inconsistent estimates of variables of interest (Chintagunta et al. 1991). However, beyond simply controlling individual consumer heterogeneity, consumer heterogeneity can be the basis for market segmentation, targeting, positioning, and micro-marketing as one of the most fundamental concepts in marketing strategy (Kamakura et al. 1996). Therefore, a well-developed statistical approach to account for heterogeneity may provide researchers with the opportunity to widen the understanding of online consumer shopping behavior, by identifying the effect of new constructs extracted from heterogeneity – e.g., there would be substantial but unobserved explanatory variables in predicting online consumers’ behaviors such as “risk lover consumer” vs. “risk aversion consumer”. And also, the different online purchase behaviors are highly expected to be observed depending on the hypothesized consumer types (the segmented groups conditional on the consumer heterogeneity). The examination of different patterns by segmented groups is of direct value in optimizing the marketing interventions in customer relationship management (CRM) – by establishing the basis of how the managers take advantage of the segmented market in short and long-term strategy planning.
Given that, the main concern of this study is twofold: (1) online consumer (or market) segmentation and (2) online retailers’ product positioning strategy conditional on the identified consumer segmentation.

1.1. Online market (consumer) segmentation

Since Smith's (1956) initial article on market segmentation, the concept of market segmentation has received a lot of attention along product positioning (Green and Krieger 1991). Market segmentation is the process of identifying relatively homogeneous groups of consumers with respect to perceptions of, evaluations of, need for, and behavior toward a product or services – i.e., market segmentation is rationalized on the concept of consumer heterogeneity in their preferences (and ultimately observable choices). The ideal segmentation scheme begins by finding basis or response variables that capture the difference across customers’ heterogeneity (Manchanda 2002). A basis for segmentation is a factor that varies among groups within a market, but that is consistent within groups. The basis can be either person-by variables (e.g., demographic characteristics, psychographic characteristics, product usage, and current brand loyalties) or situational variables (e.g., type of meal in which beverage is consumed, and buying for oneself versus a gift for someone else) and their interactions (Green 1977; Green and DeSarbo 1979; Dickson 1982).

There are many clustering techniques. The underlying schema of the cluster analysis is comparable to not only controlling consumer heterogeneity but also consumer segmentation. Wind (1978) identifies two principal approaches: (1) priori segmentation: the researcher chooses some variable(s) of interest (e.g., demographic segmentation using age and gender, and RFM segmentation using Recency-Frequency-Monetary value) and then classifies consumers according to the designation, and (2) cluster-based segmentation (or post hoc) – person-by variable "scores" (e.g., psychographic characteristics and preferences) are clustered into person groups whose average within-group similarity is high and whose between-group similarity is low (Green and Krieger 1991; Rust and Verhoef 2005). Previous studies employing either priori segmentation or cluster-based segmentation follow ad-hoc (or static) categorization procedures based on metric(s) measured at time $t$, not reflecting the heterogeneity in the
longitudinal pattern based on metrics measured at time 1, 2, …, \( t \). That is, while managers want to ensure that segments will be comparable over time for a long term prospecting plan, the segmentation technique previously developed cannot reflect on the change of the behavior of every group segmented and require stability in the group structure – comparability over time –, in order for managers to implement the techniques for business purposes.

Our plan is to achieve consumer segmentation based on the longitudinal “pattern” of online consumer shopping behaviors. Market segmentation based on the consumers’ developmental purchasing pattern is expected to provide us with more accurate consumer clustering than static clustering analysis because the clustering enables us to remove the effect of the time-specific noise that would be observed at a particular time period. Furthermore, the segmentation based on longitudinal pattern will allow us to predict how consumers behave even at time \( t+1 \), which is the most interesting time period for managerial implication. In this study, we examine online consumers’ purchasing pattern across the groups identified based on “a homogeneous trajectory within a group and heterogeneous trajectories between groups.” Specifically, we aim to segment consumers based on the trajectories of the hypothesized consumer characteristics, by operationally defining the conceptual characteristics with observed behavioral measurements. There are three branches of methodology for analyzing individual-level developmental trajectories: (1) hierarchical modeling, (2) latent curve analysis, and (3) trajectory analysis. These advanced methods allow researchers to move beyond the use of ad hoc categorization procedures for constructing developmental trajectories. Whereas the hierarchical and the latent curve methodologies are suitable for modeling typical patterns of growth that vary regularly through the population (with multivariate continuous distribution functions), trajectory analysis assumes that the population is composed of a mixture of distinct groups identified (group-based approach and using a multinomial modeling) by their developmental trajectories (Nagin 1999). A trajectory method is useful for modeling unobserved heterogeneity in a population, where trajectories vary greatly across population subgroups both in terms of the level of behavior at the outset during the measurement period and the rate of growth
and decline over time (Nagin 1999). Therefore, in this study, we are using trajectory model as a clustering technique.

1.2. Retailer’s product positioning

All market segmentation approaches ultimately consider both facets: consumer characteristics vs. product attributes (Green and Krieger 1991). Market segmentation and product positioning are very closely related, as buyers and sellers seek mutual accommodation in product or service offerings that best satisfy preference and profit objectives. Then, retailers can react to each segmented group by selecting (introducing) the best products, whose attributes are best matched to the segmented groups, respectively. Here, we build a practical framework for an optimal product positioning strategy on the basis of the trajectory based-segmented consumer groups. Given consumer segmentation acquired from trajectory analysis, we will describe and illustrate how we can (1) match product attributes and segmented group characteristics and (2) build product positioning framework for managerial purposes. Our schema eventually enables us to calculate two sets of probabilities, which provides an operational capability for implementing product positioning strategy: (1) who will be most interested in a certain product – that is, who the manager promotes (or advertise) the product to – and (2) the (relative) probability of how much a certain product will appeal to consumers. These probabilities may be used for tactical decision making (product selection/positioning), in particular when a manager introduces a new product to their online malls.

In the next section, we describe the framework of “consumer segmentation and product positioning” along with (1) a brief review of the main components of trajectory analysis and (2) the operational procedure of positioning. In section 3, we describe the data and measurement. In section 4, we discuss the empirical results of trajectory analysis and illustrate the framework with the real data. In the subsequent section, we discuss the main insight from our findings, limitation and future research direction.

2. Conceptual Framework and methods
2.1. Consumer segmentation and product positioning

Figure 1 is a schematic diagram of the proposed “trajectory-based consumer segmentation and product positioning” framework.

**Hypothesized Consumer Types**
Risk loving vs. risk aversion shopper
Big money vs. small money shopper
Frequent vs. occasional online shopper

**Operational Definitions** ($k$ dimensions)
- Average Intangibility Level (AIL)
- Average Price
- Number of transactions in a unit of time

**Operational Definitions**

**Individual Transaction Data ($Y_i$)**
- Time variant factors
- Time invariant factors

**Trajectory Analysis**
(Clustering technique based on online shopping pattern)

**Consumer Segmentation**

**Operational Definitions**

**Product Attribute**
Product ($p$) attribute in a dimension $k$: $Attr_{p,k}$

**Matching between group and product**
Calculating the probability of how well a product $p$ is matched to an identified group $j$ on a dimension $k$: $Pr_{j,p,k}$

**Bayesian Inference**
Updating the probability that product $p$ is appealing to consumer $i$, on $k$ multiple dimensions

Probability that a product, $p$ is appealing to consumer $i$: $Pr_{i,p}$

**Computing the probability that product $p$ is appealing to consumer $i$ on a dimension $k$: $Pr_{i,p,k}$**

**Projecting the characteristic of group $j$ on a dimension $k$ at the next period $t+1$: probability distribution of $Attr_{j,k,t+1}$**

**Identifying group $j$ based on a dimension $k$, conditional on $Y_i$: a homogeneous trajectory within a group and heterogeneous trajectories between groups: ($j|k$)**

**Probability that individual $i$ belongs to group $j$ segmented based on a dimension $k$: $P(j|Y_i,k)$**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

**Operational Definitions**

As stated, we are using the trajectory analysis that enables us to identify consumer groups on
hypothesized (multiple) consumers’ inherent characteristics: (1) risk loving vs. risk averse online consumer, (2) online big money vs. online small money consumer, and (3) frequent vs. occasional online consumer. Our approach – the application of trajectory analysis into the market segmentation context – represents an important refinement to the common practice of market segmentation in that (1) it can incorporates measures commonly used in previous segmentation (e.g., frequency and monetary values RMF Cells – priori segmentation), (2) it can reflect the product attribute of average intangibility level as person-by "score" variable – which is a psychographic characteristic (post-hoc segmentation) –, and (3) it addresses the comparability problem over time, which is the weakness of other techniques.

As shown in Figure 1, we first identify the groups of individual consumers following similar progression of online shopping behavior. Here, we assume that we can operationalize the hypothesized consumer characteristics with observable consumer shopping pattern over time (e.g., risk loving vs. risk averse shoppers from average intangibility level (AIL) calculated from all products a consumer purchases in a unit of time window (to be discussed in detail). Then, individual transaction data (including time-invariant characteristics of consumers and time-varying factors) is used for the trajectory analysis based on the operational definitions.

We execute a trajectory analysis in multiple dimensions, which are interesting to managers of online malls. So, every consumer probabilistically belongs to multiple groups as many as the number of dimensions \( k \). For example, a particular consumer \( i \) can be identified as “frequent online shopper” with 85% probability (based on the dimension of “# of transactions in a unit of time”) and simultaneously “big money online shopper” with 54% probability (based on average price of product individual consumer purchases.)

Second, once the first step of clustering (trajectory analysis) is done, the product positioning model is applied to find consumers who are most likely to be interested in a product, given exogenous product attributes. The design of matching product attributes and individual characteristics is to maximize the effectiveness of marketing interventions (e.g., email campaign and advertising) by searching for a pre-

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44 In this study, \( k = 3 \). But this can extend to as many as observables.
existing consumer(s)\textsuperscript{45} who is/are most likely to purchase a selected product (we will discuss the product position mechanism in the next section.)

Two additional considerations underlie the framework. First, our schema will be mainly applied to online malls handling products of diverse product spectrum in terms of price and AIL. Also, we assume that managers are interested in who to target a certain product at (Bult and Wansbeek 1995; Gönül and Hofstede 2006; Nash 2000; Rust and Verhoef 2005). Second, we assume that once managers find the best match between a product profile and individual characteristics extracted from identified consumer groups, individual marketing can be installed with targeted email campaigns (Dreze 2006) or dynamically generated Web content depending on the matching information – the differentiation of the first display on the web (e.g., www.amazon.com).

The symbols used throughout the paper and the variables they represent are listed in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i$</td>
<td>Consumer index</td>
</tr>
<tr>
<td>$j$ or $s$</td>
<td>Identified group index</td>
</tr>
<tr>
<td>$p$</td>
<td>Product index</td>
</tr>
<tr>
<td>$k$</td>
<td>Dimension index for consumer segmentation</td>
</tr>
<tr>
<td>$t$</td>
<td>Calendar time (1, 2, …T)</td>
</tr>
<tr>
<td>$IL_p$</td>
<td>Intangibility level of product $p$ (See the measurement section)</td>
</tr>
<tr>
<td>$y_{it}$</td>
<td>Measurement of consumer $i$ at time $t$ on a dimension $k$</td>
</tr>
<tr>
<td>$NT_{it}$</td>
<td># of transactions of consumer $i$ at time $t$</td>
</tr>
<tr>
<td>$AIL_{it}$</td>
<td>Average intangibility level of consumer $i$’s market basket at time $t$</td>
</tr>
<tr>
<td>$AP_{it}$</td>
<td>Average price of consumer $i$’s market basket at time $t$</td>
</tr>
<tr>
<td>$Y_{ik}$</td>
<td>$[y_{i1k}, y_{i2k}, \ldots, y_{ikt}]$</td>
</tr>
<tr>
<td>$\pi_{jk}$</td>
<td>Proportion of the population comprising group $j$ on a dimension $k$</td>
</tr>
<tr>
<td>$P_j(y_{it})$</td>
<td>Probability (distribution function) of observing $y_{it}$ at time $t$ given membership in group $j$</td>
</tr>
<tr>
<td>$P_k(Y_i)$</td>
<td>Probability (distribution function) of observing $Y_i$ given membership in group $j$</td>
</tr>
<tr>
<td>$P(Y_i)$</td>
<td>Unconditional probability (distribution function) of observing $Y_i$</td>
</tr>
<tr>
<td>$P(j</td>
<td>Y_i)$</td>
</tr>
<tr>
<td>$Attr_{p,k}$</td>
<td>Attribute of product $p$ on dimension $k$</td>
</tr>
<tr>
<td>$Attr_{j,k,t+1}$</td>
<td>Probability distribution of behavior measurements observed in group $j$ on dimension $k$, at time $t+1$</td>
</tr>
<tr>
<td>$Pr_{j,p,k}$</td>
<td>Probability of how well a product $p$ is matched to an identified group $j$ in terms of a product attribute dimension $k$</td>
</tr>
<tr>
<td>$Pr_{i,p,k}$</td>
<td>Probability that a product $p$ is appealing to a consumer $i$ on product attribute dimension $k$</td>
</tr>
</tbody>
</table>

\textsuperscript{45}The “preexisting” is required because our method is based on consumers’ shopping history (pattern-based clustering technique).
2.2. Trajectory-based consumer segmentation

We aim to classify a set of consumers into two or more mutually exclusive unknown groups based on their online shopping pattern over time – the goal of cluster analysis is to organize consumers into groups in such a way that the degree of similarity is maximized for the items within a group and minimized between groups. The trajectory analysis is a semi-parametric, group-based approach for identifying distinctive groups of individual trajectories within the population and for profiling the characteristics of group members (Jones et al. 2001; Nagin 1999; Nagin 2005). It is an innovative technique in the cluster-based method and has provided valuable insights in studying not only physical aggression among youth and criminal careers but also information systems (IS) research (e.g., web utilization and saturation patterns, and IT-based application adoption behavior (Christ et al. 2001; Zheng et al. 2003).

The Trajectory model enables us to: (1) identify rather than assume distinctive groups of trajectories, (2) articulate the shape of the trajectory (e.g., rising, falling, stable, or hump-shaped) for each trajectory group, (3) estimate the proportion of the population following each trajectory group, (4) estimate the group membership probability that the individual belongs to each trajectory group, and (5) relate group membership probability to individual characteristics and circumstances (Nagin 1999; Nagin 2005). All of them are examined for our first research goal (exploring online consumers’ shopping pattern) and the capabilities of 1, 2, and 4 are mainly used on our proposed framework of “group-based consumer segmentation and product positioning.” which is the second research goal in the study.

A brief overview of the statistical theory underlying the method is given below. Trajectory analysis models the linkage between time and behavior by assuming polynomial relationships. A cubic relationship (either linear or quadratic is possible) is given as:

\[ y_{it} = \beta_0 + \beta_1 \text{period}_{it} + \beta_2 \text{period}_{it}^2 + \beta_3 \text{period}_{it}^3 + \varepsilon_{it} \]  

(1)
, where \( y_{it} \) is a consumer \( i \)'s behavior measurement at time \( t \), and \( \epsilon_{it} \) is a disturbance assumed to be normally distributed with zero mean and constant variance \( \sigma^2 \). For the censored normal distribution, we can write the probability distribution function of \( y_{it} \), given the membership in group \( j \) as:

\[
\begin{align*}
\Pr_j(y_{it} = c_{\text{min}}) &= \Phi\left( \frac{c_{\text{min}} - \left( \beta_0^j + \beta_1^j \text{period}_{it}^1 + \beta_2^j \text{period}_{it}^2 + \beta_3^j \text{period}_{it}^3 \right)}{\sigma} \right) \\
\Pr_j(y_{it} = c_{\text{max}}) &= 1 - \Phi\left( \frac{c_{\text{max}} - \left( \beta_0^j + \beta_1^j \text{period}_{it}^1 + \beta_2^j \text{period}_{it}^2 + \beta_3^j \text{period}_{it}^3 \right)}{\sigma} \right) \\
\Pr_j(y_{it}) &= \frac{1}{\sigma}\phi\left( \frac{y_{it} - \left( \beta_0^j + \beta_1^j \text{period}_{it}^1 + \beta_2^j \text{period}_{it}^2 + \beta_3^j \text{period}_{it}^3 \right)}{\sigma} \right)
\end{align*}
\]

, where \( \phi \) and \( \Phi \) are the density function and the cumulative distribution of a normal random variable with mean, \( \beta_0^j + \beta_1^j \text{period}_{it}^1 + \beta_2^j \text{period}_{it}^2 + \beta_3^j \text{period}_{it}^3 \). \( c_{\text{min}} \) and \( c_{\text{max}} \) are the boundaries of censored normal distribution. By permitting \( \beta_m^j \) (denoting \( \beta_m \) in \( j \) group) to vary freely across trajectory groups, the model provides the capability for identifying the shape of the trajectories of every group. The vector \( Y_i = [y_{i1}, y_{i2}, \ldots, y_{iT}] \) denotes the longitudinal sequence of individual \( i \)'s behavioral measurement, \( y_{it} \) during the \( T \) periods. \( P_j(Y_i) \) denoting the probability (distribution function) of observing \( Y_i \) conditional on group \( j \) membership is formulated:

\[
P_j(Y_i) = \prod_{t=1}^{T} \Pr_j(y_{it})
\]

(2)

The unconditional probability of observing \( Y_i \) equals the sum across the \( J \) groups of the probability of observing \( Y_i \) given membership in group \( j \), weighted by the proportion of the population in group \( j \), \( \pi_j \).

\[
P(Y_i) = \sum_j \left( \pi_j P_j(Y_i) \right) = \sum_j \left( \pi_j \prod_{t=1}^{T} \Pr_j(y_{it}) \right)
\]

(3)

For given \( j \), the conditional independence is assumed for \( y_{it} \) over the \( T \). Thus, the likelihood for the entire sample of \( N \) consumers is:
The parameters of interest ($\beta_m^j$, $\pi_j$ and $\sigma$) can be estimated by maximum likelihood estimation (MLE). The maximization is performed using a general Quasi-Newton procedure. It should be noted that the model parameters may differ from cluster to cluster, which is the key feature of this method since it allows for identification of population heterogeneity not only in the level of behavior at a given stage but also in its development over time.

### 2.2.1. Group membership probabilities

We can calculate the probability of individual membership in the groups that make up the model – trajectory model does not determine definitively an individual's group membership. Specifically, for each individual $i$, the probability of membership in group $j$ is calculated based on the estimated coefficient. We denote this probability by $P(j | Y_i)$. The posterior group membership probability is:

$$
\hat{P}(j | Y_i) = \frac{\hat{P}(Y_i | j) \hat{\pi}_j}{\sum_j \hat{P}(Y_i | j) \hat{\pi}_j} 
$$

(5)

where $\hat{P}(Y_i | j)$ is the estimated probability of observing $i$'s actual behavioral trajectory, $Y_i$ given membership in $j$, and $\hat{\pi}_j$ is the estimated proportion of the population in group $j$. The quantity $\hat{P}(j | Y_i)$ can be calculated based on the trajectory parameters estimated above. Group identification is probabilistic, not certain. But individuals can be assigned to the group to which their posterior membership probability is largest and thus the posterior probability calculations provide us with an objective basis for assigning individuals to the trajectory group that best matches their behavior.

### 2.2.2. Group membership and time-invariant covariates

The trajectory model allows us to relate the identified distinctive group trajectories to a set of
observables associated with individuals (time-invariant covariates called risk factors in original work) to identify the potential causal relations between individuals’ characteristics and group membership probability. Adding covariates to determine the proportion of the population in group \( j \) within trajectory equations on the assumption that \( \pi_j \) varies based on individual demographic factor (age and gender), we can see how observable factors distinguish the populations of the various trajectory groups. Let \( X_i \) denote a vector of factors that are potentially linked to group membership assignment. Then a multinomial logit model (Maddala 1983) to estimate \( \pi_j \) is:

\[
\pi_j(X_i) = \frac{\exp(X_i\theta_j)}{\sum_j \exp(X_i\theta_j)}
\]  

(6)

, where parameters \( \theta_j \) captures the impact of the covariates of interest, \( X_i \), on the probability of membership in group \( j \). Because \( \theta_j \) is typically set to zero for one contrast group, the estimated coefficients for other groups are interpreted as measuring the impact of covariates on group membership relative to the contrast group – they measure how the group membership probability in a group varies as a function of each of the risk factors. Given that, we can conclude that some of risk factors significantly increase (or decrease) the probability of membership in the trajectory group relative to contrast group. Accordingly, they also decrease (or increase) the probability of membership in the contrast group relative to compared group membership. Individual-level likelihood function is:

\[
P(Y_i) = \sum_j \left[ \frac{\exp(X_i\theta_j)}{\sum_j \exp(X_i\theta_j)} \prod_j p_j(y_{ij}) \right]
\]  

(7)

It is noticeable that model estimation is not a two-stage process in which the trajectories are first estimated and then in a second stage we predict \( \pi_j \) on \( X_i \). They are estimated simultaneously with the \( \beta \) parameters of key interest that describe the form of each group’s trajectory.

2.2.3. Trajectories and time-varying covariate
We can analyze whether events that occur during the course of a trajectory might alter the trajectory itself – we can analyze main key dependent variables controlling other time-varying variables. The addition of time varying independent variables is for the purpose of testing for whether there is an enduring impact of the variables on the selected dependent variable. We derive the next regression equations, adding TVC (time varying covariate) in equation (1):

\[ y_{it} = \beta_0^i + \beta_1^j \text{period}_{it} + \beta_2^i \text{period}^2_{it} + \beta_3^i \text{period}^3_{it} + \alpha_j^iTVC_{-1it} + \ldots + \alpha_n^iTVC_{nit} + \epsilon_{it} \]  

(8)

Here, we can test formally and statistically the impact of the time-varying covariates on the shape of the trajectories with \( \alpha \) coefficients.

2.2.4. Dual trajectory analysis

Beyond trajectory of a single outcome, the trajectory model enables us to consider the joint probability of group memberships – probability of consumer \( i \)'s belong to the group \( j \) and group \( s \) simultaneously – in two dependent variables. The linking probabilities provide a far more detailed and varied summary of the developmental connections between the two outcomes that are evolving contemporaneously (Nagin 2005). Suppose that the \( j \) trajectories groups for \( Y_1 \) are probabilistically linked \( s \) trajectory groups for \( Y_2 \), the joint probability of membership in trajectory group \( j \) for \( Y_1 \) and \( s \) trajectory groups for \( Y_2 \) is:

\[
P(Y_{1it}, Y_{2is}) = \sum_j \sum_s \left( \prod_j p_j(y_{1it}) \prod_s p_s(y_{2is}) \right)
\]

(9)

2.3. Product positioning (matching of product attributes and individual characteristics)

As a motivating example of how a product positioning is used, consider a product email campaign. Many ISMs have been using email campaigns because it is a cheap and faster way to reach their customers. But email campaigns would be considered to be spam mail to many consumers as well as
the response rate being extremely low. This is the main reason we have to rely on product positioning or direct marketing – ISMs select the right customer (or group) for given product attributes – in order to find an effective and efficient email campaign. The techniques of direct marketing have been developed diversely through a dynamic programming approach or a regression model (Bult and Wansbeek 1995; Gönlü and Höfstede 2006; Nash 2000). Here, we develop a new product positioning approach based on the matching of product attributes and individual characteristics extracted based on trajectory group segmentation. It is worthwhile to reiterate that the inputs required for the product positioning implementation are: (1) the statistics and probabilities acquired from the trajectory analysis and (2) the metrics calibrating product attributes on the same (or comparable) dimensions as behavior measurements, $y_{it}$, which are dependent variables in the trajectory analysis. The calibration of consumer-product relations in our framework requires four steps – through which we calculate probabilities in a sequence – providing us with information of who will be most interested in a certain product.

2.3.1. Projecting a group behavior at time $t+1$

Once a group-based trajectory analysis is done, we will complete trajectory equation of each group: $\hat{y}_{ij} = \hat{\beta}_{0} + \hat{\beta}_{1}\text{period}_i^j + \hat{\beta}_{2}\text{period}_i^j + \hat{\beta}_{3}\text{period}_i^j$ (e.g., Table 4, 5, and 6). Trajectory estimation of every group is based on the time horizon from 1 to $t$. We can project the probability distribution of $\hat{y}_{i+1}$, of group $j$, at the next period, $t+1$, in product attribute dimension $k$. Let us use $\text{Attr}_{j,k,t+1}$ instead of $\hat{y}_{i+1}$ in order to easily indicate the comparison between product attributes and group characteristics, adding subscript $k$ indicating dimension, and renaming $y$ into $\text{Attr}$ standing for Attribute. $\text{Attr}_{j,k,t+1}$ is assumed to be normally distributed with a mean value of $\overline{\text{Attr}}_{j,k,t+1}$, which is equal to $\hat{y}_{i+1}$, and the variance of $\text{var}($$\text{Attr}_{j,k,t+1})$. Here, $\text{var}($$\text{Attr}_{j,k,t+1})$ can be predicted two ways: (1) we can use the estimated $\sigma^2$ because trajectory analysis is build on the assumption of homoskedasticity across both $j$ and $t$, or (2) we can approximate it with the variance of behavior measurements observed in group $j$ identified on dimension $k$ at time $t$. As a result, the trajectories of every group at $t+1$ are characterized in terms of the estimated
mean and the estimated variance in the distribution. The distribution of \( \text{Attr}_{j,k,t+1} \) changes across \( t \) as well as across \( j \).

### 2.3.2. Matching between a product attribute and a group characteristic on dimension \( k \)

Here, we calibrate the extent to which a particular product characterized by \( \text{Attr}_{p,k} \) (attribute of product \( p \) on dimension \( k \)) is matched to \( \text{Attr}_{j,k,t+1} \) (the characteristics of the identified groups at time \( t+1 \)). The strength of the link between product attributes and group characteristics is calculated in terms of probability. This study suggests two metrics:

1. based on geometric distance

   \[
   \Pr_{j,p,k}(\text{Attr}_{j,k,t+1}, \text{Attr}_{p,k}) = \left( 1 - \frac{\text{Attr}_{j,k,t+1} - \text{Attr}_{p,k}}{\sum_{j=1}^{J} (\text{Attr}_{j,k,t+1} - \text{Attr}_{p,k})} \right) / J \tag{10-1}
   \]

2. based on probability mass function:

   \[
   \Pr_{j,p,k}(\text{Attr}_{j,k,t+1}, \text{Attr}_{p,k}) = \int_{\text{Attr}_{p,k} - \varepsilon}^{\text{Attr}_{p,k} + \varepsilon} \frac{\exp\left(-\frac{(x - \text{Attr}_{j,k,t+1})^2}{\text{Var}(\text{Attr}_{j,k,t+1})}\right)}{2\pi\sqrt{\text{Var}(\text{Attr}_{j,k,t+1})}} \, dx \tag{10-2}
   \]

### 2.3.3. Matching between a product attribute and an individual characteristic on dimension \( k \)

We calculate the probability of individual membership in the group \( j \) on dimension \( k \). Given that, we will describe how to compute the probability that a product is appealing to a consumer \( i \) on a dimension \( k \). Then we are using two probabilities: (1) \( \hat{P}(j \mid Y_i) \): the probability of membership in group \( j \) for each individual \( i \) (see equation 5) and (2) \( \Pr_{j,p,k}(\text{Attr}_{j,k,t+1}, \text{Attr}_{p,k}) \) calculated in step 2.

\[
\Pr_{i,p,k} = \sum_{j=1}^{J} \left( \hat{P}(j \mid Y_i) \times \Pr_{j,p,k}(\text{Attr}_{j,k,t+1}, \text{Attr}_{p,k}) \right) \tag{11}
\]

We can easily calculate the probability, using equation 5:

\[
\Pr_{i,p,k} = \sum_{j=1}^{J} \left( \frac{\hat{P}(Y_i \mid j) \hat{P}(j)}{\hat{P}(Y_i)} \times \Pr_{j,p,k}(\text{Attr}_{j,k,t+1}, \text{Attr}_{p,k}) \right) \tag{12}
\]
2.3.4. Updating product appealing probability on multi-dimensions

In step 3, we calculate the probability that a product $p$ is appealing to consumer $i$, on only one dimension $k$. We repeat $K$ times the procedures from step 1 through step 3 on different dimensions. Using Bayesian inference with the probabilities calculated in multiple dimensions, we can acquire the probability that overall, a product $p$ is appealing to consumer $i$. The number of dimensions of interest is equivalent to the number of Bayesian updating. The updating procedure is formulated as:

$$ Pr_{i,p} = \frac{Pr_{i,p,k} \times Pr_{old}}{Pr_{i,p,k} \times Pr_{old} + (1 - Pr_{i,p,k}) \times (1 - Pr_{old})} \text{, where } Pr_{old} = \text{old probability} \tag{13} $$

3. Data and measurement

Our research site (www.hmall.com) is one of the premier ISMs in Korea. The main data source for this study is the transaction data of the randomly selected consumers, who bought at least one item every unit of time of six months at the ISM from January 2002 to June 2006 (2435). We can get the information of (1) individual demographics (age and gender) and (2) product attributes (product category, price, and transaction date), with respect to every transaction. Given the information, we can trace individual purchasing history.

We aim to analyze hypothesized different longitudinal shopping patterns based on the three consumer types: (1) risk loving vs. risk aversion shopper, (2) big money vs. small money shopper, and (3) frequent vs. occasional online shopper. To achieve the research goal, we, first, operationalize the unobservable consumer types with the following three metrics: (1) average intangibility level ($AIL$), (2) Average Price ($AP$), and (3) the number of transactions ($NT$) – referring to the metrics developed to measure product-level uncertainty (Kim et al. 2007). Second, we examine the trajectories of the three behavior measurements.\textsuperscript{46}

\textsuperscript{46} Actually, we tried to identify groups based on the highest price, which is one of the four metrics. The highest price of a market basket does not show a homogeneous trajectory within a group and heterogeneous trajectories between groups.
The metrics are calculated from individual $i$’s market basket composing multiple items purchased at the unit of time $t$: (1) $AIL_i = \sum_{n=1}^{N} IL_{nt} / N$, (2) $AP_i = \sum_{n=1}^{N} Price_{nt} / N$, and (3) $NT_i$: the number of purchased products in time $t$. Unlike $AP$ and $NT$, $AIL$ requires the prerequisite assignment of the intangibility level ($IL_p$) on every product. Product intangibility is a measure of the difficulty encountered by an online consumer in assessing the fit between his/her requirements and the features of a product – equivalently, the measured extent to which information of a product can be digitally transferred or how critical the loss of physical cue is – (Degeratu et al. 2000; Kamakura and Russell 1993; Lal and Sarvary 1999; McCabe and Nowlis 2003). We matched one of five $IL$s – from 1(most tangible) through 5(most intangible) – to every product. Clothing and shoes are common examples of products that have high intangibility levels (see the Kim et al. 2007 for the details).

Trajectory analysis enables us to choose the probability distribution that is best suited to the data. Suitably defined probability distributions are used to handle 3 data types with specific distributional assumption, respectively: (1) Poisson distribution for count data, (2) logistic distribution for binary data, and (3) (censored) normal distribution for psychometric scale data. In particular, the censored normal model is useful for modeling the conditional distribution of psychometric scale data that tend to cluster at the minimum and the maximum of the scale. We model the above three metrics of interest with censored normal distribution, which should be the most appropriate data types. For example, average price is analyzed with the censored normal model by specifying a minimum and a maximum that lie outside the range of the observed data values, because we do not observe clustering at extremes.

<table>
<thead>
<tr>
<th>Data Type</th>
<th>User Type (conditional on)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NT, AIL, AP</td>
<td>Censored normally distribution</td>
</tr>
</tbody>
</table>

Table 5.2. Measurement and data type

4. Results

A key step in model estimation is the selection of the number of trajectory groups that best fit the data. Model selection was basically based on the Bayesian Information Criterion (BIC) and Bayes factors
(refer to online appendix). Specifically, models ranging from two to five groups were estimated. Additionally, we allowed the order of each of the trajectories to vary between zero (flat), first (constantly rising or declining), second (rising or falling at different rates) and third (changing directions). Table 3 shows the number of groups and the estimated proportion. We find interestingly that estimated trajectories do not overlap at any time in all three behaviors.

<table>
<thead>
<tr>
<th>Group #</th>
<th>Estimated proportion (%) and labeling</th>
<th>Noticeable patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td>NT</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>87.5 (NT1: occasional online shopper)</td>
<td>Higher response group shows higher increasing pattern while lowest response group shows constant pattern</td>
</tr>
<tr>
<td></td>
<td>11.8 (NT2: moderate online shopper)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.7 (NT3: frequent online shopper)</td>
<td></td>
</tr>
<tr>
<td>AIL</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>31.2 (AIL1: risk aversion shopper)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>48.3 (AIL2: risk neutral shopper)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>22.5 (AIL3: risk lover shopper)</td>
<td></td>
</tr>
<tr>
<td>AP</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>95.2 (AP1: online small money shopper)</td>
<td>Higher response shows higher increasing pattern while lower response decreasing</td>
</tr>
<tr>
<td></td>
<td>4.8 (AP2: online big money shopper)</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.3. Summary of marginal developmental trajectories

4.1. The number of transactions in a unit of time (NT)

We identify three distinct trajectories for the number of individual transactions in a unit of time (refer to the Table 4 for estimated coefficients). These trajectories are shown in Figure 2. The solid lines represent actual behavior and the dashed lines show predicted behavior.
The largest group follows a horizontal line trajectory without significant upward or downward trend (approximately 87.49% of the population) at relatively lower shopping frequency (less then 10 transactions per six months). There are two more frequent online shopper groups (moderate online shopper and frequent online shopper). The frequent online shopper group (0.7%) follows a high-rising trajectory along with more frequent shopping behavior, which rises steadily through the period. Moderate shopper group shows a low-rising trajectory occupying 11.80% of the population. As obviously shown, increasing pattern of trajectories is proportional to the frequency of online shopping – the more frequently a consumer purchases online in a unit of time, the more increasing the number of items purchased is over the period.

As we described for the proposed product positioning framework, the predicted group behavior at time $t+1$ will be used for selecting the group best suitable for a specific product. Then, the upward trends that both moderate online shopper and frequent online shopper groups show will be substantial in projecting the behavior at time $t+1$ – a general ad-hoc clustering technique cannot yield a statistical tool for inferring the future behavior. Therefore, we can build product-positioning framework based on more accurate projection than technique not reflecting dynamic trend.
<table>
<thead>
<tr>
<th>Group</th>
<th>Estimated Parameter</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>NT1</td>
<td>$\beta_0$</td>
<td>6.57***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>2.43***</td>
</tr>
<tr>
<td>NT2</td>
<td>$\beta_0$</td>
<td>14.46***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>2.43***</td>
</tr>
<tr>
<td>NT3</td>
<td>$\beta_0$</td>
<td>30.24***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>11.28***</td>
</tr>
<tr>
<td></td>
<td>$\sigma$</td>
<td>11.33***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group membership probability</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NT1 (%)</td>
<td>87.49***</td>
</tr>
<tr>
<td>NT2 (%)</td>
<td>11.80***</td>
</tr>
<tr>
<td>NT3 (%)</td>
<td>0.69***</td>
</tr>
</tbody>
</table>

BIC=-69315.31196 (N=19480)  BIC=-69306.99419 (N=2435)  AIC=-69283.80339

*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$

Table 5.4. The estimated result of NT-based trajectory analysis

### 4.2. Average intangibility level (AIL)

We identify three distinct developmental trajectories of AIL in a unit time (refer to Figure 3 and Table 5). The composition ratios of three groups are relatively evenly distributed compared to NT-based trajectories. The results show that the relationship between AIL and the strength of increasing pattern is significantly related as well. The largest group labeling risk neutral shopper follows a moderate rising trajectory occupying 48.25% of the population while the second largest groups (31.2%) does not show significant variation of AIL during the periods. The other group comprising 20.54% of the population shows a steeper increasing pattern. As we mentioned, our trajectory analysis is based on consumers consistently purchasing online (at least one purchase in 6 months). But the second largest group showing no change in AIL gives us interesting insight concerning consumer online shopping behavior – recall that we trace individual purchasing history over a period of four and half years. The members belonging to the group enjoy online shopping steadily but the products purchased is limited into the only highly tangible items (the intercept coefficient = 2.63). Given different trends, we can conclude that consumers purchasing more intangible items tend to expand the product spectrum toward more intangible products over time while consumers purchasing mainly tangible items are highly likely to restrict the spectrum of online-purchased products into highly tangible product even though time goes and they increase online shopping experience.
Table 5.5. The estimated result of AIL-based trajectory analysis

<table>
<thead>
<tr>
<th>Group</th>
<th>Estimated Parameter</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIL1</td>
<td>$\beta_0$</td>
<td>2.63***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>-0.18***</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>0.04***</td>
</tr>
<tr>
<td></td>
<td>$\beta_3$</td>
<td>-0.002***</td>
</tr>
<tr>
<td>AIL2</td>
<td>$\beta_0$</td>
<td>3.14***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>0.03**</td>
</tr>
<tr>
<td></td>
<td>$\beta_3$</td>
<td>-0.001*</td>
</tr>
<tr>
<td>AIL3</td>
<td>$\beta_0$</td>
<td>3.71***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>$\beta_3$</td>
<td>0.0006</td>
</tr>
<tr>
<td></td>
<td>$\sigma$</td>
<td>0.74***</td>
</tr>
</tbody>
</table>

Group membership probability

<table>
<thead>
<tr>
<th>Group</th>
<th>(%)</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIL1</td>
<td>31.20***</td>
<td>1.79</td>
</tr>
<tr>
<td>AIL2</td>
<td>48.25***</td>
<td>1.58</td>
</tr>
<tr>
<td>AIL3</td>
<td>20.54***</td>
<td>1.15</td>
</tr>
</tbody>
</table>

BIC=-27014.67394 (N=21915)  BIC=-26998.19476 (N=2435)  AIC=-26954.71199

*Significant at $p < 0.05$  ***Significant at $p < 0.01$  ****Significant at $p < 0.001$

4.3. Average price (AP)

Figure 4 displays the result of the trajectory analysis of the average price of an individual market basket as a response variable. Two groups were identified: a group called “online big money shoppers”
was composed of consumers who show a relatively high average price of a market basket (refer to the Table 6). This group accounts for an estimated 4.8% of the sample population. A second group called “online small money shoppers” of individuals showing low average price is estimated to constitute the majority of consumers (95.2%). Online shoppers purchasing relatively cheap products show a slight downward trajectory while consumers purchasing relatively expensive products are likely to purchase more expensive products over time.

Figure 5.4. Marginal trajectories of Average Price

<table>
<thead>
<tr>
<th>Group</th>
<th>Estimated Parameter</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP1</td>
<td>$\beta_0$</td>
<td>34064.98***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>31908.51***</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>-3210.55***</td>
</tr>
<tr>
<td>AP2</td>
<td>$\beta_0$</td>
<td>188866.57</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>-5485.08</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>2411.50</td>
</tr>
<tr>
<td></td>
<td>$\sigma$</td>
<td>124701.98***</td>
</tr>
</tbody>
</table>

BIC=-288698.8332 (N=21915) BIC=-288690.0443 (N=2435) AIC=-288666.8535

The analysis is based on Korean currency (won). $1$ is roughly equivalent to ￦1000

*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$

Table 5.6. The estimated result of AP-based trajectory analysis
4.4. Group membership probability and individual demographic factors

The response segments (identified groups) can be profiled using individual demographic factors. The group profiles are reported in Table 7, which are based on a simple collection of uni-variate contrasts (see the online appendix for graphical comparison).

<table>
<thead>
<tr>
<th>Variables</th>
<th>#</th>
<th>NT1</th>
<th>NT2</th>
<th>NT3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>2046</td>
<td>0.868</td>
<td>0.127</td>
<td>0.006</td>
</tr>
<tr>
<td>Male</td>
<td>342</td>
<td>0.912</td>
<td>0.076</td>
<td>0.012</td>
</tr>
<tr>
<td>Age &lt;30</td>
<td>288</td>
<td>0.885</td>
<td>0.108</td>
<td>0.007</td>
</tr>
<tr>
<td>30&lt;= Age &lt;40</td>
<td>1422</td>
<td>0.883</td>
<td>0.113</td>
<td>0.004</td>
</tr>
<tr>
<td>40&lt;= Age &lt;50</td>
<td>591</td>
<td>0.851</td>
<td>0.134</td>
<td>0.015</td>
</tr>
<tr>
<td>50&lt;= Age</td>
<td>134</td>
<td>0.873</td>
<td>0.127</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>#</th>
<th>AIL1</th>
<th>AIL2</th>
<th>AIL3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>2,046</td>
<td>0.259</td>
<td>0.514</td>
<td>0.227</td>
</tr>
<tr>
<td>Male</td>
<td>342</td>
<td>0.556</td>
<td>0.348</td>
<td>0.096</td>
</tr>
<tr>
<td>Age &lt;30</td>
<td>288</td>
<td>0.285</td>
<td>0.549</td>
<td>0.167</td>
</tr>
<tr>
<td>30&lt;= Age &lt;40</td>
<td>1,422</td>
<td>0.340</td>
<td>0.485</td>
<td>0.176</td>
</tr>
<tr>
<td>40&lt;= Age &lt;50</td>
<td>591</td>
<td>0.261</td>
<td>0.479</td>
<td>0.261</td>
</tr>
<tr>
<td>50&lt;= Age</td>
<td>134</td>
<td>0.224</td>
<td>0.425</td>
<td>0.351</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variables</th>
<th>#</th>
<th>AP1</th>
<th>AP2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Female</td>
<td>2,046</td>
<td>0.958</td>
<td>0.042</td>
</tr>
<tr>
<td>Male</td>
<td>342</td>
<td>0.892</td>
<td>0.108</td>
</tr>
<tr>
<td>Age &lt;30</td>
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</tr>
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<td>0.064</td>
</tr>
<tr>
<td>50&lt;= Age</td>
<td>134</td>
<td>0.963</td>
<td>0.037</td>
</tr>
</tbody>
</table>

Table 7. Group profiles

Table 7 is the first step in addressing the causal relationship of interest but indeed only a beginning. There is another way developed for analyzing the impact of the time-invariant covariates in trajectory analysis, where a multivariate procedure is used to sort our redundant predictors for the purpose of constructing a more parsimonious list of predictors or for causal inference based on equation 7.

Table 8 reports the results of an analysis based application of the multinomial logit-based likelihood function (or binary logit-based likelihood function). The model examines the relationship of the probability of group membership to two classic risk factors (age and gender) for three online shopping behaviors, respectively. In a model that specifies group membership probability as a function of individual-level characteristics, no single base-rate probability is estimated for each group. For this analysis, each estimated coefficients measure how the individual factor influences the probability of
membership in the particular trajectory group relative to membership in a specified comparison group. NT1, AIL1, and AP1 serve as the comparison group for this model. A positive coefficient estimate for a specific trajectory group implies that the associated variable increases the probability of membership in the group relative to the comparison group. Conversely, a negative coefficient implies a decreased relative probability.

| Variables | # of transactions
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NT1</td>
<td>NT2</td>
<td>NT3</td>
</tr>
<tr>
<td>Constant</td>
<td>-</td>
<td>-2.57 (0.35) ***</td>
</tr>
<tr>
<td>Sex</td>
<td>-</td>
<td>-0.53 (0.19) ***</td>
</tr>
<tr>
<td>Age</td>
<td>-</td>
<td>0.017 (0.009) **</td>
</tr>
</tbody>
</table>

| Variables | Average Intangibility Level
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AIL1</td>
<td>AIL2</td>
<td>AIL3</td>
</tr>
<tr>
<td>Constant</td>
<td>-</td>
<td>0.38 (0.34)</td>
</tr>
<tr>
<td>Sex</td>
<td>-</td>
<td>-1.24 (0.14) ***</td>
</tr>
<tr>
<td>Age</td>
<td>-</td>
<td>0.01 (0.008)</td>
</tr>
</tbody>
</table>

| Variables | Average Price
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AP1</td>
<td>AP2</td>
</tr>
<tr>
<td>Constant</td>
<td>-</td>
</tr>
<tr>
<td>Sex</td>
<td>-</td>
</tr>
<tr>
<td>Age</td>
<td>-</td>
</tr>
</tbody>
</table>

Multi-nominal logit coefficients are shown and standard errors are shown in parentheses. NT1, AIL1, and AP1 are comparison groups in each model.

*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$

Table 5.8. The impact of individual profile on Group membership probabilities

The parameter estimates describing the shapers of the trajectories are not reported in Table 8 – they predict trajectories that are virtually identical to those reported in Figure 2, 3, and 4. We found that the results provide support for the anticipation that the individual demographic profile is a predictor for membership in identified groups, even though these statistical tests leave unanswered other questions about whether these same individual characteristics are distinguished among the non-contrast trajectory groups – this questions can be answered with the conventional z-score-based procedure or Wald test (Wald 1943). We, however, found inconsistent ordering of the estimated coefficients of each risk factor in size (e.g., sex: NT2 = -0.53 and NT3 = 0.60), indicating a relatively big heterogeneity in the composition of each trajectory.

Summarizing Table 8, older consumers are more likely than younger consumers to be the
member of AIL3 (risk loving shopper, coefficient is 0.05, p=0.009). This relationship may result from either the income effect based on the assumption that the older has a greater income than the younger or presumably, inherent association between the age and the need for purchasing more intangible products such as clothing. Also, we found that (1) one more unit of age increases the probability of being NT2 showing moderate purchasing frequency relative to NT1, (2) female consumers are more likely than the male consumers to purchase more intangible and more expensive products, and (3) male consumers are more likely than the female consumers to belong to NT1 showing lowest purchasing frequency.

4.5. The impact of time-varying covariate to the trajectories

The group-based trajectory framework is not immune to the hazards of drawing causal inferences from non-experimental data (Nagin 2005). In our research context of online shoppers’ behaviors, the most salient obstacle to causal inference is distinguishing cause from effect – for example, does the increase of AIL cause the increase of AP? or reciprocally the increase of AP is the antecedent predictor for the increase of AIL? In econometric modeling, such relationships can yield problems of endogeneity. The failure to account for endogeneity can seriously compromise statistical findings due to confounding cause-and-effect relationship (Wooldridge 2002). But, the three online shopping behaviors are characterized by the individual market basket at the same time $t$ and so the three response variables are measured simultaneously. Our main focus is the relationship among three metrics based on a market basket rather than the causal relationships.

We identify trajectories of one behavior, selecting the other two variables as covariates response based on equation 8. This approach may illuminate the relationship of three variables. The results of the analysis are reported in Table 9, 10, and 11.

<table>
<thead>
<tr>
<th>Group</th>
<th>Estimated Parameter</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>NT1</td>
<td>$\beta_0$</td>
<td>4.53***</td>
</tr>
<tr>
<td></td>
<td>AIL</td>
<td>0.86***</td>
</tr>
<tr>
<td></td>
<td>AP</td>
<td>0.00***</td>
</tr>
<tr>
<td>NT2</td>
<td>$\beta_0$</td>
<td>2.14</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>2.16***</td>
</tr>
<tr>
<td></td>
<td>AIL</td>
<td>4.18***</td>
</tr>
</tbody>
</table>
Table 5.9. The estimated result of NT-based trajectory analysis with time varying covariate

<table>
<thead>
<tr>
<th>Group</th>
<th>Estimated Parameter</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIL1</td>
<td>$\beta_0$</td>
<td>2.63***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>-0.16**</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>0.038**</td>
</tr>
<tr>
<td></td>
<td>$\beta_3$</td>
<td>-0.002**</td>
</tr>
<tr>
<td></td>
<td>NT</td>
<td>0.002**</td>
</tr>
<tr>
<td></td>
<td>AP</td>
<td>0.00***</td>
</tr>
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<td>AIL2</td>
<td>$\beta_0$</td>
<td>3.14***</td>
</tr>
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<td>$\beta_1$</td>
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<td></td>
<td>$\beta_2$</td>
<td>0.019</td>
</tr>
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<td></td>
<td>$\beta_3$</td>
<td>-0.0008</td>
</tr>
<tr>
<td></td>
<td>NT</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>AP</td>
<td>0.00***</td>
</tr>
<tr>
<td>AIL3</td>
<td>$\beta_0$</td>
<td>3.84***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>0.05</td>
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<td></td>
<td>$\beta_2$</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>$\beta_3$</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>NT</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>AP</td>
<td>0.00***</td>
</tr>
</tbody>
</table>

Group membership probability

<table>
<thead>
<tr>
<th>Group</th>
<th>(%)</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIL1</td>
<td>31.32238***</td>
<td>1.77939</td>
</tr>
<tr>
<td>AIL2</td>
<td>48.79198***</td>
<td>1.57718</td>
</tr>
<tr>
<td>AIL3</td>
<td>19.88564***</td>
<td>1.13661</td>
</tr>
</tbody>
</table>

BIC=-26895.21962 (N=21915)  BIC=-26872.14877 (N=2435)  AIC=-26811.27289
*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$

Table 5.10. The estimated result of AIL-based trajectory analysis with time varying covariate

<table>
<thead>
<tr>
<th>Group</th>
<th>Estimated Parameter</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP1</td>
<td>$\beta_0$</td>
<td>35450.88***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>28305.26***</td>
</tr>
<tr>
<td></td>
<td>$\beta_2$</td>
<td>-2941.00***</td>
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<tr>
<td></td>
<td>NT</td>
<td>41.22</td>
</tr>
<tr>
<td></td>
<td>AIL</td>
<td>2730.80</td>
</tr>
<tr>
<td>AP2</td>
<td>$\beta_0$</td>
<td>194323.59***</td>
</tr>
<tr>
<td></td>
<td>$\beta_1$</td>
<td>3868.51</td>
</tr>
</tbody>
</table>

BIC=-26895.21962 (N=21915)  BIC=-26872.14877 (N=2435)  AIC=-26811.27289
*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$
Table 5.11. The estimated result of AP-based trajectory analysis with time varying covariate

<table>
<thead>
<tr>
<th></th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
<th>$\beta_7$</th>
<th>$\beta_8$</th>
<th>$\beta_9$</th>
<th>$\beta_{10}$</th>
<th>$\beta_{11}$</th>
<th>$\beta_{12}$</th>
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</thead>
<tbody>
<tr>
<td>NT</td>
<td>-2369.71***</td>
<td>1600.80</td>
<td>917.17</td>
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<td></td>
</tr>
<tr>
<td>AIL</td>
<td>-6214.11</td>
<td>545.81</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>124263.22***</td>
<td>917.17</td>
<td>545.81</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Group membership probability

<table>
<thead>
<tr>
<th></th>
<th>(%)</th>
<th>(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP1</td>
<td>93.79***</td>
<td>0.51</td>
</tr>
<tr>
<td>AP2</td>
<td>6.20***</td>
<td>0.51</td>
</tr>
</tbody>
</table>

BIC=-288664.8663 (N=21915)  BIC=-288651.6829 (N=2435)  AIC=-288616.8967

The analysis is based on Korean currency (won). $1 is roughly equivalent to ₩1000

*Significant at $p < 0.05$  **Significant at $p < 0.01$  ***Significant at $p < 0.001$

Table 12 summaries the relationship between the three outcomes.

<table>
<thead>
<tr>
<th></th>
<th>NT1</th>
<th>NT2</th>
<th>NT3</th>
<th>AIL1</th>
<th>AIL2</th>
<th>AIL3</th>
<th>AP1</th>
<th>AP2</th>
</tr>
</thead>
<tbody>
<tr>
<td>TVC: time varying covariate</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NT</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>+</td>
<td>+</td>
<td>X</td>
<td>X</td>
<td>-</td>
</tr>
<tr>
<td>AIL</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>.</td>
<td>.</td>
<td>.</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>AP</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>.</td>
<td>.</td>
</tr>
</tbody>
</table>

+$ = $positively significant, $-$ = negatively significant, $X = $insignificant

Table 5.12. The summary of the impact of time-varying covariates

In all NT-based identified groups, we found that AIL makes each trajectory move up. In both AIL1 and AIL2 groups, we found that NT makes each trajectory move up (NT is not significant in AIL3). The positive relationship between AIL and NT is consistent with our anticipation that there is an expansion of product spectrum from increase of market basket in size. Also, we can infer that the expansion of product spectrum in terms of AIL and price results in more frequent online transaction.

Even though we found that the increase of AP induced the higher trajectory in the AIL-based trajectory and the NT-based trajectory, the estimated coefficients are almost zero. Only one coefficient of covariates is significant among in AP-based identified groups, which is NT in AP2. Consumers with high willingness to pay online expand the product spectrum toward relatively cheap product lines as they purchase more items online.
4.6. Results from the dual trajectory model

Here, we estimated three dual trajectory models (3 combinations of three response variables of online consumer behaviors). Trajectories estimated based on dual trajectory models are very similar to marginal trajectories (or equivalently, the estimated parameters describing the shapes of the trajectories) reported in Figure 2, 3, and 4. In each dual trajectory analysis, the results can be expressed as three alternative representations of the linkage between two online consumer behaviors: Two conditional probabilities and joint probability.

4.6.1. NT and AIL

Here, the estimated (conditional or joint) group membership probabilities are shown in Table 13. The members of NT1 (occasional shopper) are more likely to be members of AIL1 (risk aversion shopper) than members of AIL3 (risk lover shopper). As shown in all three representations of the linkage, this interrelationship is remarkable in all probability distribution (e.g., \( \pi_{AIL1|NT1} > \pi_{AIL3|NT1} \) and \( \pi_{AIL1|NT3} < \pi_{AIL3|NT3} \)). But, we did not find the consistent ordering of the probabilities. For example, \( \pi_{AIL1|NT1} < \pi_{AIL2|NT1} \) and \( \pi_{AIL2|NT1} > \pi_{AIL3|NT1} \). Considering everything, we cannot conclude that the interrelationship between NT group membership and AIL group membership is not clear, even despite the small probability supporting a mutual dependency of the memberships. This may result from great heterogeneity in the developmental course of AIL – practically, AIL2 (risk neutral shopper) accounts for the largest portion of the population.

This heterogeneity across group memberships supports the usefulness of Bayesian updating (step 4 in product positioning framework) on multiple dimensions. That is, if the rank of probabilities of individual memberships to groups on one dimension \( k \) is proportionate to that on another dimension \( s \) in order, then, we may extract the most information about the consumer’s shopping behavior from only one behavioral measurement (the probability of group memberships on one dimension). For example, suppose that occasional shoppers always show risk aversion behavior, then information of the consumer’s being
occasional shoppers (or risk aversion shopper) on one dimension is enough to characterize the shopper. But as Table 13 says, the consistent shopping pattern is not observed, so that we can increase the effectiveness of our product positioning framework by incorporating the information of consumers’ shopping pattern on more dimensions.

| Probability of group NT\(_k\) conditional on group AIL\(_j\) (\(\pi_{k|j}\)) | AIL1 | AIL2 | AIL3  |
|-----------------------------|----------|--------|--------|
| NT1                         | 92.9     | 87.6   | 78.8   |
| NT2                         | 6.4      | 12.2   | 18.5   |
| NT3                         | 0.7      | 0.3    | 1.8    |

| Probability of group AIL\(_j\) conditional on group NT\(_k\) (\(\pi_{j|k}\)) | AIL1 | AIL2 | AIL3  |
|-----------------------------|----------|--------|--------|
| NT1                         | 33.1     | 48.3   | 18.5   |
| NT2                         | 16.8     | 49.4   | 33.8   |
| NT3                         | 29.8     | 17.8   | 52.2   |

<table>
<thead>
<tr>
<th>Joint Probability of group AIL(_j) and group NT(<em>k) ((\pi</em>{j,k}))</th>
<th>AIL1 (31.2)</th>
<th>AIL2 (48.3)</th>
<th>AIL3 (22.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NT1 (87.5)</td>
<td>29.0</td>
<td>42.3</td>
<td>16.2</td>
</tr>
<tr>
<td>NT2 (11.8)</td>
<td>2.0</td>
<td>5.9</td>
<td>4.0</td>
</tr>
<tr>
<td>NT3 (0.7)</td>
<td>0.2</td>
<td>0.1</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Table 5.13. The interrelationship between NT and AIL

4.6.2. NT and AP

Compared to the interrelationship between NT and AIL, the relationship between NT and AP is more clear. Table 14 shows a strong interrelationship between trajectories for two shopping behavioral measurements (NT and AP). Given the estimated group membership probability, we found their association somewhat counter-intuitive. The consumers purchasing relatively expensive products (AP2, online big money shopper) are likely to purchase less frequently. In other words, “frequent online shoppers” are more likely to be members of AP1 (online small money shopper) than “occasional online shoppers” are. Indeed, their probability of membership with respect to AP2 and NT3 is nearly zero (see \(\pi_{AP2|NT3} = \pi_{NT3|AP2} = \pi_{NT3,AP2} = 0\)).

Given that, we can infer that consumers are likely to purchase relatively cheap products as they increase the size of a market basket. This finding gives us insight of online consumers’ shopping behavior – the price spectrum of products purchased online is heading more strongly for cheap product lines than
for expensive product lines as the size of a market basket increases. Actually, this finding is consistent to
the finding of Kim et al. (2007) – online shopping experience decreases average price – on the clear
condition that online shopping experience is positively related to period.

And also, this finding might enable us to predict the change of consumer group membership
based on Kim et al.‘s finding (2007) that cumulative online shopping experience increases the number of
transactions in unit time. Therefore, as online consumers move to the NT3 group, we can conjecture the
increase of AP1 in a relative proportion. And also, this prediction is comparable to their finding that
consumers are likely to expand a product spectrum toward a relatively cheap product line, based on the
negative significant influence of cumulative online shopping experience on AP in the regression model.

| Probability of group AP<sub>k</sub> conditional on group NT<sub>j</sub> (π<sub>k|j</sub>)            |
|-----------------|-----------------|-----------------|
|                 | NT1             | NT2             | NT3             |
| AP1             | 94.6            | 97.8            | 100             |
| AP2             | 5.1             | 2.1             | 0.0             |

| The Probability of group NT<sub>k</sub> conditional on group AP<sub>j</sub> (π<sub>j|k</sub>) |
|-----------------------------------------------|-----------------|-----------------|
| AP1           | NT1             | NT2             | NT3             |
|               | 87.1            | 12.2            | 0.7             |
| AP2           | 94.5            | 5.5             | 0.0             |

| Joint Probability of group AP<sub>j</sub> and group NT<sub>k</sub> (π<sub>j,k</sub>) |
|----------------------------------------|-----------------|-----------------|
| AP1 (95.2)                             | NT1 (87.5)      | NT2 (11.8)      | NT3 (0.7)      |
| AP2 (4.8)                              | 82.9            | 11.6            | 0.7            |
|                                        | 4.5             | 0.3             | 0.0            |

Table 5.14. The interrelationship between NT and AP

### 4.6.3. AIL and AP

We found that there is an inconsistent ordering (e.g., π<sub>AIL|AP1</sub> and π<sub>AIL, AP1</sub>) in the relationship
between NT and AIL. There is heterogeneity in the AIL-based trajectory given AP and so we have to be
cautious of concluding the interrelationship between AIL group membership and AP group membership.

But, Table 15 shows a very intriguing distribution. For members of AP2, the probability of their
following any specific AIL group is far more certain than for the AP1 group. In particular, the probability
of group AIL<sub>k</sub> conditional on group AP<sub>j</sub> shows clear distinction of distributions. The conditional
probability of π<sub>AIL|AP2</sub> accounts for 75.9% while π<sub>AIL|AP1</sub> is relatively spread. This result indicates that
online big money shoppers are highly likely to be risk aversion shoppers, showing the existence of the
product-level uncertainty (Kim et al. 2007). When a consumer belongs to the big online money shopper group, the consumer is more likely to be a risk aversion shopper. When a consumer purchases an expensive product without physically checking the product in the online market, the consumer has to embrace risk as much as product price. The risk varies according to the product attribute (or product information available online) among the products of the same price. Given the result, we can infer that online big money consumers reduce the risk by purchasing structured (highly tangible) products.

| Probability of group APₖ conditional on group AILᵢ (πₖ|ᵢ) |
|----------------------------------------------------------|
| AIL1 | AIL2 | AIL3 |
| AP1  | 85.1 | 97.6 | 98.6 |
| AP2  | 14.8 | 2.3 | 1.3 |

The Probability of group AILᵢ conditional on group APₖ (πᵢ|ₖ)

<table>
<thead>
<tr>
<th>AIL1</th>
<th>AIL2</th>
<th>AIL3</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP1</td>
<td>27.7</td>
<td>50.5</td>
</tr>
<tr>
<td>AP2</td>
<td>75.9</td>
<td>19.4</td>
</tr>
</tbody>
</table>

Joint Probability of group APₖ and group AILᵢ (πᵢₖ)

<table>
<thead>
<tr>
<th>AIL1 (31.2)</th>
<th>AIL2 (48.3)</th>
<th>AIL3 (22.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP1 (95.2)</td>
<td>26.1</td>
<td>47.5</td>
</tr>
<tr>
<td>AP2 (4.8)</td>
<td>4.5</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Table 5.15. The interrelationship between AIL and AP

4.7. Illustrative application

An empirical example should help clarify the proposed approach. Our illustrative application shows the effectiveness of our product positioning strategy based on the estimated result. We select clothing at $250 for illustration example – product price of $250 and intangibility level 5 –. Following procedure described above, we finally acquire the Prᵢₚ, which is relative value, not absolute criteria (see the Table 16).

<table>
<thead>
<tr>
<th>Probability that a product, p is appealing to consumer i :</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product price: $250 (Attrₚ,AP) and Intangibility level: 5(Attrₚ,AIL)</td>
</tr>
<tr>
<td>AIL1</td>
</tr>
<tr>
<td>2.5</td>
</tr>
<tr>
<td>Prᵢₚ,AIL</td>
</tr>
<tr>
<td>0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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<tbody>
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<td>0.0018</td>
<td>1.0000</td>
<td>0.0000</td>
<td>0.0557</td>
<td>0.1243</td>
<td>0.008303793</td>
</tr>
<tr>
<td>2</td>
<td>0.0013</td>
<td>0.9622</td>
<td>0.0365</td>
<td>0.9957</td>
<td>0.0043</td>
<td>0.0614</td>
<td>0.1259</td>
<td>0.009338677</td>
</tr>
<tr>
<td>3</td>
<td>0.9614</td>
<td>0.0386</td>
<td>0.0000</td>
<td>0.9987</td>
<td>0.0013</td>
<td>0.0099</td>
<td>0.1248</td>
<td>0.001418536</td>
</tr>
</tbody>
</table>
As shown in Figure 8, we can see that probability varies across individuals. It is expected that managers can position this product using the calculated probability. For example, managers can use email campaigns for the product to consumers, whose probability is more than a certain value in order to maximize the effectiveness of the email campaign and at the same time minimize the bad impact of spam mail. If the threshold is set at 0.02, it is the best choice to select 9 consumers with higher probability among the
42 consumers (refer to the Figure 8). And we also confirmed the variation of matching between an individual and a product across product attributes.

![Appealing probability](image)

Figure 5.5. Illustration of appealing probabilities across users

5. Discussion and conclusion

We find that all group trajectories are distinguished by both intercepts and the developmental trend (the shape of trajectories). That is, we find interestingly that trajectories do not overlap at any time in all three behaviors. This provides us valuable insight in analyzing and predicting consumer types. We can infer that every group has a distinctive feature and the characteristics can be used for group based consumer segmentation at any point.

The members of “heavy shopper (NT3)” group purchase, on average, around 15 items per month online, whereas members in the other two groups purchase at most a few items online. The heavy shopper group is estimated to include about 0.7% of the population in our research period covering 2002 through 2006. The members of NT3 group purchase around 2 items per month, occupying the around 89%. We might infer from this finding that online shopping does not seem to substitute offline shopping even despite of appealing and attractive strength over the offline market. The uniqueness of our data should be supplemented by research based on other data sets.
Our framework for product positioning can be used with multiple products. But the current framework does not reflect the interrelationship between multiple products. Future study should generalize the framework by incorporating the cross effect of products.

Although we show the distinction of the pattern by distinct group and suggest a product positioning mechanism, the proposed approach does not cover strategy formulation across all aspects of the marketing mix. Given the distinctive trajectories by groups, managers are interested in how to change the direction of trajectory for business objectives. Then, advertising, sales promotion, and distribution efforts may usually be considered to be the trigger of the change. Future research should analyze how to change the identified pattern for specific purposes such as the inducement of more transaction.

Finally, we should check how effective the proposed framework works – with performance measures regarding email campaign and Web content differentiation depending on the appealing probability calculated from the proposed framework. Many ISMs have implemented tracking technologies for email campaigns or can accurately measure when a customer responds to the emails. In the case of Web content differentiation, the click-through rates or website stickiness can be implemented to test the appeal of content (Bucklin and Sismeiro 2003).
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