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망외부성이 디지털 경제의 마케팅에 미치는 영향에 관한 연구

A Study on the Effect of Network Externality on Marketing in the Digital Economy

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Abstract

With more sectors showing increasing returns, we are in need of modified concepts, models, and strategies for management in today's digital economy. In chapter 2, this study incorporates network externality factors into marketing analysis in the digital economy. Total network size, local network size, and network strength are introduced and I found three network externality factors have different effects on the users' future usage intention for the four Internet services. In chapter 3, I developed a new diffusion model that incorporates the indirect network externality. New model incorporates the two-way interactions in forecasting the diffusion of hardware products based on a simple but realistic assumption. The new model is parsimonious, easy to estimate, and does not require more data points than the Bass diffusion model. The model was applied to forecast sales of DVD players in the United States and in South Korea, and to the sales of Digital TV sets in Australia. When compared to the Bass and NSRL diffusion models, the new model showed better performance in forecasting long-term sales.

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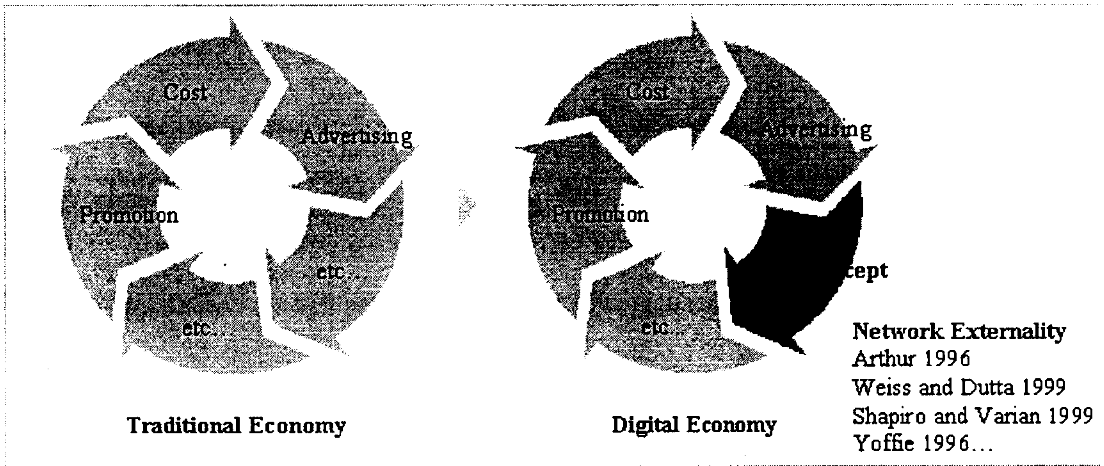
Chapter 1 Introduction

With more sectors showing increasing returns, we are in need of modified concepts, models, and strategies for management in today's digital economy. Traditional economic concepts are not enough to explain new issues in the digital economy in effective ways. Some errors or gaps could be aroused if we analyze digital economic problems without consideration of new digital economic variables. For reducing these errors or gaps, some researchers have started to explore and introduce new digital economy concepts. Network externality is suggested as one of the most important concepts we should consider in understanding the digital economy (Arthur, 1996; John, Weiss and Dutta, 1999; Shapiro and Varian, 1999; Yoffie, 1996).

For some product categories, utility of a product depends on the number of consumers who have adopted the product. For some others, it depends on the availability of complementary products. The former effect is referred to as *direct* network externality while the latter as *indirect* network externality in the literature. Direct network externality arises when the consumer utility of using a product or service increases with the number of users of that product or service (Economides, 1996a; Farrell and Saloner, 1985; Katz and Shapiro, 1985, 1986). Prominent examples with direct network externality include fax, telephone, online instant messenger service, etc. On the other hand, indirect network externality involves products of which consumer utility depends on the availability of complementary products and services (Church and Gandal, 1993; Farrell and Saloner, 1985; Gupta, Jain and Sawhney, 1999; Shankar and Bayus, 2002). Typically, the indirect network externality effect is observed in such product categories as computer, DVD player, home video game, and digital TV.

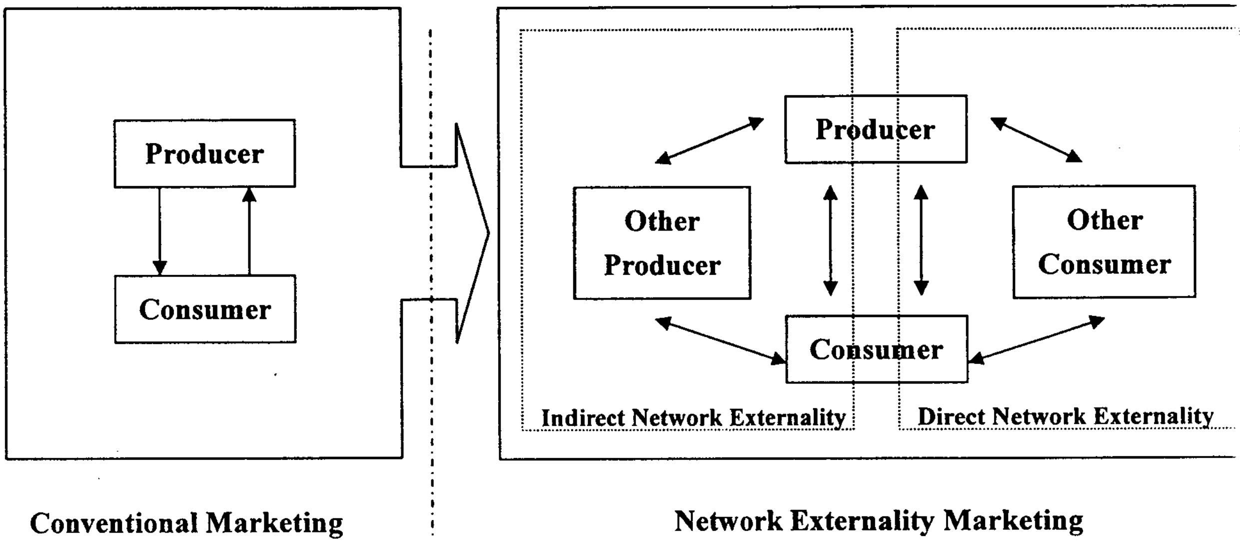
Theoretical investigations on network externality started mostly in 1980s in the field of economics. They mainly focused on how influencing factors on network externality, such as product compatibility or standardization decisions, affect the market equilibrium and social welfare (Church and Gandal, 1993; Economide, 1996a, 1996b; Farrell and Saloner, 1985; Katz and Shapiro, 1985, 1986; Kim, 2002; Matutues and Regibeau, 1988). On the other hand, empirical studies of network externality mainly focused on demonstrating the existence of effects of network externality or compatibility (Basu, Mazumdar and Raj, 2003; Brynjolfsson and Kemerer, 1996; Gandal, 1994; Gupta, Jain and Sawhney, 1999; Nagard-Assayag and Manceau, 2001; Shankar and Bayus, 2003).

We may expect effective marketing strategies if we consider the concept of network externality into the marketing problems in the digital economy. So far in traditional economy, some traditional marketing variables such as advertising, promotion, cost etc. explained most of traditional marketing problems well. However, in the digital economy, new concepts such as network externality should be also included for the effective analysis in the digital economy as shown in Figure 1-1. Network externality is now one of the core concepts in analyzing business problems like the traditional variables such as cost, advertising, promotion etc. did in the past.



<Figure 1-1> Traditional Economy Vs. Digital Economy

The importance of considering network externality in marketing in the digital economy can also be explained by the change of marketing environment. In general, conventional marketing can be defined as the exchanging and creating values between producer and consumer like shown in left side of figure 1-2. However, most products or services could not exist in isolation in the complex digital economy environment. We also have to consider other producers of complementary products and other consumers using the same product like shown in right side of figure 1-2. Number of interactions we should consider increase as network externality is greater. And this is why we have to consider network externality when we analyze marketing problems in digital economy.



<Figure 1-2> Comparison between Conventional and Network Externality Marketing

In sum, marketers need different strategies from those applied to traditional markets where the economy is characterized by decreasing returns. This study will develop new models that incorporate one of key concepts in the new digital economy, i.e., network externality. Such models will be especially helpful to marketers of product categories characterized by increasing returns. Incorporating this new concept into marketing models will also provide opportunities and challenges for research in marketing in the digital economy.

In Chapter 2, this study investigates the effects of three direct network externality factors on the users' future usage intention of the network services. Past literature of direct network externality focused on effects of total network size on the success of a network. I try to refine the concept of direct network externality in this chapter. In the following chapter, this study develops a new model that can predict sales for markets that show indirect network externality. Specifically, I develop a model that incorporates indirect network externality into the diffusion model framework. Then, I discuss theoretical and managerial implications as well as limitations and possible further extensions of the research.

Chapter 2 The Effects of Direct Network Externality on the Future Usage of Internet Services

Researchers in various academic fields have investigated effects of network externalities such as economics, management science and marketing (Basu *et al.*, 2003; Brynjolfsson and Kemerer, 1996; Church and Gandal, 1993; Gandal, 1994; Gupta *et al.*, 1999; Kim, 2002; Lee and O'Connor, 2003; Matutues and Regibeau, 1988; Shankar and Bayus, 2003). They commonly suggest that a company with the greatest installed base will eventually take all the market. The "winner takes all" concept implies that *total network size* is the most important network externality factor that determines the success of network services.

I agree that the total network size is a critically important factor in early markets with the network externality. However, I suggest that users' satisfaction with a network service and two other network externality factors are also important determinants for success of the network service. The main focus of this chapter is to investigate the effects of two additional network externality factors, local network size and network strength, on the members' future usage intention for four popular Internet services, i.e., online messenger, online community, chat room and email services. I empirically show that local network size and network strength plays important but different roles for the four online services.

The chapter is organized as follows. I first explain two additional network externality factors as well as total network size. I also present a model that explains the future usage of a network service incorporating these factors and users' satisfaction with network services. Next, I develop research hypotheses for four representative Internet services. Then, I empirically investigate differences in the importance of the network externality factors for different Internet services. Finally, I close this chapter with discussion on its contributions and managerial implications.

2.1 Network Externality Factors

A common understanding in the network externality literature is that total network size is *the* powerful competitive advantage. A firm which has taken advantage of building a larger installed base in the early stage of a product market is expected to dominate the market (Katz and Shapiro, 1985, 1986; Farrel and Saloner, 1985; Matutes and Regibeau, 1988; Church and Gandal, 1993; Economides, 1996a,1996b; Kim, 2002; Gandal, 1994; Brynjolfsson and Kemerer, 1996; Shankar and Bayus, 2003).

However, there are cases where market followers with smaller network sizes catch up with market leaders who have larger network sizes. For example, in the United States, AOL quickly built its installed base in the early stage of the online messenger market. It was expected to dominate the market. However, according to a MSN product manager, MSN messenger was serving 29.5 million people by February 2001, serving more people than AOL who were serving 29.1 million (Geek.com, 2001). In the Japanese home video game industry, Nintendo actually got ahead of Sega despite its lower initial market share (Shankar and Bayus, 2003). In the messenger service market of South Korea, Nate-On messenger became the leader in terms of the number of individual visitors by July 2005, passing MSN who dominated the early stage of the market (www.metrixcorp.com). All three cases were observed in product markets where network externalities are extremely important. These cases show that the total network size alone could not ensure the on-going success in such markets.

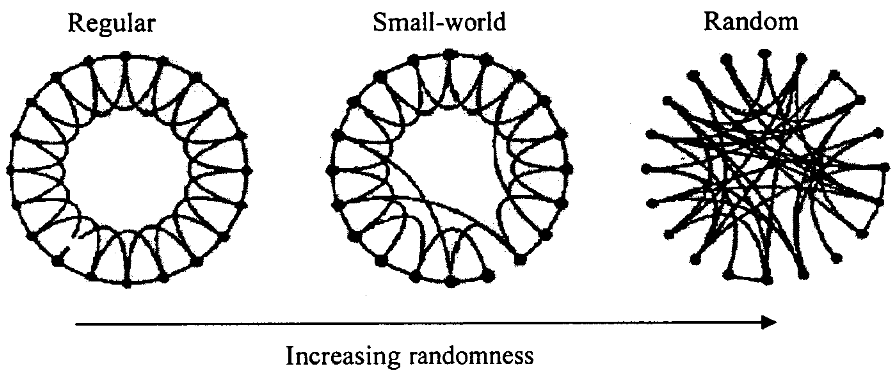
Therefore, we need to identify other factors including other network externality factors than total network size that affect the success of networks. In this chapter, I focus on network characteristics related to 'interaction among network members' along with total network size. I identify two interaction factors, one representing its width and the other representing the depth, as shown in Table 2-1. In the following, I discuss expected effects of total network size, local network size and network strength.

Table 2-1. Network Externality Factors

Network Externality Factors	
Width of interactions in a network	**Total Network Size**
	Local Network Size
Depth of interactions in a network	**Network Strength**

2.1.1 Total versus Local Network Size

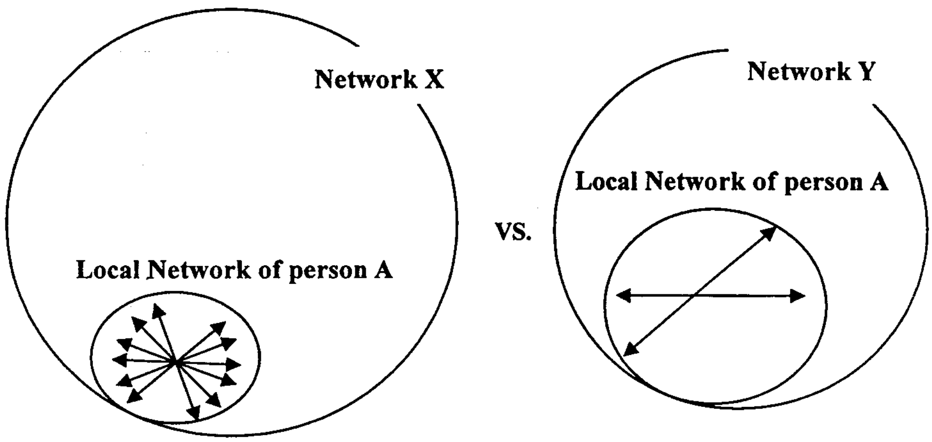
Typically, consumers in a network do not interact with everyone in the network. For example, online messenger users typically communicate with their close friends, family members, or co-workers, who are on their buddy lists. In this case, size of active members in the buddy list will be more important than that of the total network size for the users. On the other hand, users in certain networks interact with a great number of members including with who they are not familiar. For example, users of a telephone service interact with not only intimate people but also unfamiliar members in the network. They can interact with any members unless calls are refused by receivers. In such networks, total network size may become extremely important for the success of the networks. However, even in this case, a consumer may mostly communicate with his or her intimate persons limiting the number of users he or she interacts actively. Watts and Strogatz (1998) proposed possible structures of the network as shown in Figure 2-1. In a random network where every node is connected to every other node, a member can interact with everyone in the network. In a regular network where a node is connected directly to only a few relatively close nodes, a member typically interact mostly with highly overlapping acquaintances in the network. In a small-world network, a member is open to interactions with less familiar members in the network. In small world or regular networks, members mostly interact with a limited portion of networks. Thus, size of the active network could be as important as or more important than the size of the total network in many networks. I call the active network that is typically smaller than the total network a *local network.*

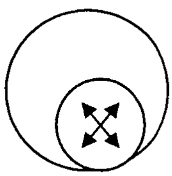


< Figure 2-1> Watts and Strogatz (1998): Typology for Social Networks

Depending on the structure of a network, importance of the local network size will be different. Suppose there are two competing networks, X and Y, in a market as shown in

Figure 2-2. Network X has a larger total network size than network Y. However, local network size of person A is larger in network Y than in network X. Typically, size of the total network could be of importance to person A if he or she seeks future expansion of his or her local network. On the other hand, person A may get higher utility from network Y than network X if he or she considers the local interactions more important.





- Larger Size of outer (inner) circle indicates larger Total (Local) Network Size
- Lots of arrows indicates higher Network Strength

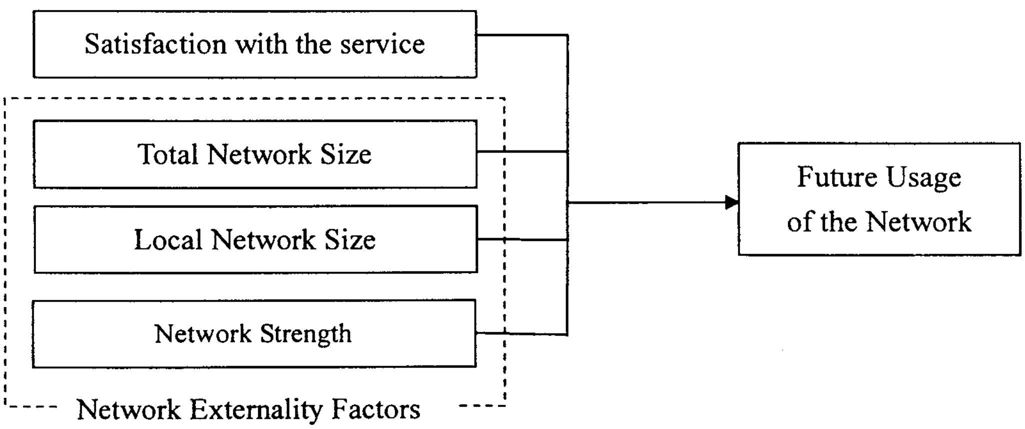
<Figure 2-2> Possible Interactions within a Network

2.1.2 Network Strength

I suggest that network strength is another crucial network externality factor that influences the future usage of a network. I define *network strength* as total amount of interactions consumers make in a certain period of time. While total and local network sizes deal with the width, network strength deal with the depth of interactions consumers make in a network. It represents the quality of interactions a member participates in the network. If someone spends more time in a network making more interactions with other members in network X than Y, then the network strength of X is greater for the person than Y. The greater the strength of a network, the stronger is cohesiveness among the network members. Cohesiveness is the degree to which members are attracted to each other and are motivated to stay in a group (Keyton and Springston, 1990). When a group is more cohesive, its members are more motivated to perform well and are able to coordinate their activities better for successful performance (Cartwright, 1968; Davis, 1969; Summers *et al.*, 1988; Mullen and Cooper, 1994).

I propose that as nètwork strength of a network becomes greater, members will get higher utility from the network. Such members will be motivated to stay in the network. Figure 2-2 shows the case where network strength plays an important role. In the figure, number of arrows in a local network represents network strength. Network Y has the larger local network size than network X. However, person A shows stronger interactions in network X than Y. In this case, person A may get higher utility from network X even if his or her local network size is smaller than network Y.

Figure 2-3 summarizes our conceptual model that incorporates the three network externality factors I have proposed. The dependent variable, network success, is operationalized as future usage intention of the network among the members. Note that, along with the three network externality factors, I also include *satisfaction with the network service* as an independent variable in the model. It is well known in marketing literature that consumers' satisfaction level with a service affects their intention to use the service in the future. (Anderson and Sullivan, 1993; Bolton and Lemon, 1999; Cronin, Brady and Hult, 2000; Shemwell *et al.*, 1998; Taylor and Baker, 1994; Yu and Dean, 2001).



<Figure 2-3> Network Externality Factors and Future Usage Intention of Network Services

2.2 Research hypotheses for Internet Services

This study focuses on four different types of popular Internet services. They are online messenger, online community, chat room, and email services. These are typical online network services that users sign up to participate in the network and get utility by communicating with other members in the network. They are Internet services that exhibit typical network externality effects as consumers get higher utility as the number of users in the same network increases.

For each of the four Internet services, I propose that important network externality factors are different from those of other Internet services. If it is true, Internet service managers should understand the nature of the network externalities of their networks before they make any resource allocation decisions. I develop hypotheses for the four Internet services based on three dimensions that characterize the networks. The first dimension is *compatibility* of a network. A network is compatible if a user can interact with users who are in a different network. The second dimension is *focus* of a network. A network is internally focused if the focal concern of a network is on the well-being and development of the network members. On the other hand, a network is externally focused if the focal concern of a network is on the well-being and development of the network itself. Finally, the third dimension is *relationships* among users. An average user of a network may have close relationships with other users. Alternatively, he or she may have shallow relationships with other members in the network. The characteristics of the four Internet services with respect to the three dimensions are summarized in Table 2-2.

Table 2-2. Comparison of the Nature of Four Internet Services

	Compatibility	**Focus**	**Relationship**
Online messenger	Incompatible	Internal	Long-term & very close
Online community	Incompatible	Internal	Long-term & intermediate
Chat room	Incompatible	External	Short-term
Email	Compatible	Various	Various

First, online messenger, online community and chat room services are low on compatibility dimension as they are typically incompatible with their competing services. Because technologies used for the services are typically not compatible with those used for competing services, users have to be in the same network to interact with one another. This very property is the main reason that network externalities occur for online messenger, online community and chat room services.

Among the three services, online messenger and online community services are internally focused networks whereas chat room services are externally focused, relatively.

Internal or external focus of an organization represents whether the organization is more concerned with the well-being and development of its people or of the organization itself (Quinn and Rohrbaugh, 1983). While the concept has been proposed for typical organizations, I am applying it on networks of people enjoying Internet services. Users of online messenger and community services mainly seek for their individual benefits or pleasure interacting with their close friends, family members, or co-workers. They are very much concerned with number of close acquaintances registering in the network. Their individual benefits or pleasure can be significantly enhanced by participating actively in their local networks. In this case, size of the active members in the buddy list, i.e., local network size, rather than total network size will be more important to the users.

On the other hand, the growth of the network itself can bring high utility to users of chat room services. The users can communicate with many and a variety of people in large and well developed networks. They can get benefits or pleasure from the growth of the network itself. Thus, users are likely to put more emphasis on the total network size. Therefore, I propose the following hypotheses:

H1: Users of an online messenger service will have greater intention to use the service in the future if the size of their local network gets bigger.

H2: Users of an online community service will have greater intention to use the service in the future if the size of their local network gets bigger.

H3: Users of an online chat service will have greater intention to use the service in the future if the size of their total network gets bigger.

Another dimension of internet service characteristics is the relationship among users, i.e., whether their relationships are close and long-term or not. Users of online messengers typically have long-term and close relationships with a limited group of members that include close friends, family or co-workers. Similarly, users of online community services have long-term relationships with a limited number of members as they communicate with their friends or those who have the same interests or hobbies. However, in this case, the relationships may not be as close as those observed for users of online messengers. Users of a community may leave the community whenever their interests or hobbies are changed.

On the other hand, in chat room services, users typically make very short-term relationships with others. They can communicate with a variety of different people whenever they want, but leave the chat room whenever they want. I propose that, other things being equal, network strength can enhance future usage intention of a network service only when members have long-term relationships with others. The network strength in a network where there are long-term relationships will enhance the group cohesiveness among members motivating them to stay in the network. On the other hand, when users have short-term relationships, effect of the network strength on future usage will be relatively small. They will be mainly interested in the growth of total network size. Therefore, I state the hypotheses as follows.

H4: For online messenger services, the higher the network strength, the stronger will be the users' future usage intention for the service.

H5: For online community services, the higher the network strength, the stronger will be the users' future usage intention for the service.

Finally, an email service is compatible with other competing email services. A user who login to network X can interact with a user who login to network Y. You don't need to register in network Y to communicate with your friend who registers in network Y if you already registered in any email service network. Thus, I do not expect any significant effects of the network externality factors for email services as they are already well developed. Neither the total or local network size nor the network strength will be important for users in making decision to stay in a network. In this case, only the satisfaction with the network service among the independent variables will influence future usage intention of the network.

H6: For email services, none of the externality factors influence the users' future usage intention for the service.

2.3 Methodology

A sample of 107 MBA students at a business school in South Korea participated in the survey. Ages of the respondents ranged from 22 to 43. The mean age was 31. More than 92% of the respondents had experience in using the network services, except for chat room services. Among the respondents, 36% had experience with chat room services.

Subjects answered three items asking about levels of the network externality factors. First, to estimate local network sizes, I asked what percentage of their acquaintances such as friends, families and colleagues were using each of the four internet services we are studying. Second, I asked the respondents to guess the percentage of total internet users who might use each of the four internet services. The answer to this question was used to estimate the total size of the networks. Third, I asked the number of times the respondents log in to each of the online networks per week and the length of time they stay in each of the network once they log-in, on average. I operationalized network strength by multiplying these two answers getting the total number of hours the respondents are staying in each network per week. I also asked the overall satisfactory level of users for each of the internet services. Finally, I measured the respondents' future usage intention of the four services using a 7-point scale.

2.4 Empirical Analysis and Results

Hypotheses are tested using the following regression model:

$$FU = \beta_0 + \beta_1(SAT) + \beta_2(TOTAL) + \beta_3(LOCAL) + \beta_4(STRENGTH) + \beta_5(GENDER) + \beta_6(AGE) + \varepsilon \quad (2.1)$$

where SAT stands for satisfaction with an Internet service,

TOTAL total network size,

LOCAL local network size

STRENGTH network strength, and

FU future usage intention of the network service.

The regression model represents the relationship described in Figure 2-3. Also included covariates were AGE and a dummy variable GENDER. The same regression model was applied for each of the four Internet services. Table 2-3 summarizes the descriptive statistics of the four network externality factors, satisfaction with the services, and future usage intention.

Table 2-3. Descriptive statistics

	Online messenger		**Online community**		**Chat room**		**Email**	
	Mean	S.D.*	Mean	S.D.	Mean	S.D.	Mean	S.D.
Satisfaction	4.99	1.31	4.36	1.51	2.45	1.20	5.94	1.12
Total Size	51.80	26.30	56.70	25.10	22.37	20.82	92.96	10.07
Local Size	47.81	30.32	52.14	27.41	15.34	15.94	88.91	13.28
Network Strength	116.11	238.98	116.02	218.82	6.70	21.74	143.80	355.26
Future Usage	5.22	1.66	4.63	1.61	1.84	0.79	6.59	.97

* S.D: Standard Deviation

Total size, local size and network strength are the greatest for email services whereas they are the lowest for chat room services. Likewise, satisfaction level and future usage intention are also the greatest for email services and the lowest for chat room services. The statistics were all consistent with our expectations.

The parameter estimates and R^2 of the model are presented in Table 2-4. The estimated models are significant for all the Internet services. Also, as expected, satisfaction with a network service is significantly related to future usage intention of the service for each of the four Internet services.

Table 2-4. Regression results - Standardized coefficients

	Online messenger	Online community	Chat room	Email
SAT	.559***	.702***	.431***	.525***
TOTAL	-.077	-.099	.361**	.022
LOCAL	.215**	.144**	.117	.097
STRENGTH	.091	.134**	.102	.020
Gender	-.016	.084	-.078	-.069
Age	.019	-.102*	-.022	.014
F-statistic	17.78***	39.528***	5.069***	7.121***
R^2	.427	.596	.495	.301

*** Significant at α =0.01. ** Significant at α =0.05. * Significant at α =0.10.

In case of online messenger and online community services, local network size is significant having positive effects on future usage of the networks. Thus, H1 and H2 are supported. For these services, total network size is not significant. The result suggests that users of internally focused networks such as online messenger and online community services are highly interested in having many close friends or colleagues in the same network. On the other hand, in case of chat room service which can be classified as an externally focused network, total network size is significant having positive effects on future usage intention of the network. The result supports H3. For the service, local network size is not significant. Thus, for users of this network, total size of the network is the main source of their utility. The results suggest that, for managers of online messengers and communities, it is important to provide useful local network services for their users. On the other hand, increasing the size of the total network could be the top priority for managers of chat room services.

Providing convenient services for helping users develop personal local networks like buddy list in online messenger services is a good example. For these networks, focusing on total network size will be a mislead strategy. For example, The Nate-On messenger in South Korea has been enthusiastic with providing convenient local network services. Less focus was given to the growth of total network size. Currently, it provides a lot of complementary services including online community site and SMS (Short Message

Service). It helps users utilize their local network in effective ways. Users in Nate-On messenger can visit their own and friends' blog site without logging into the blog site. Also, the messenger automatically finds the messenger ID's of their friends when they send SMS to their friends who are not yet in the buddy list. Nate-On messenger became the leader in this industry in terms of the number of individual visitors by July 2005, passing MSN who used to dominate the early stage of the market (www.metrixcorp.com).

Network strength is significant for online community services having positive effects on future usage intention of the network, but not for online messenger services. Thus, H5 is supported but H4 is not. It may imply that network strength is an important determinant only when the closeness level of relationships among users is intermediate. For most users of online messengers who have already developed close relationships with actively interacting members, network strength may not be relevant for determining their future usage of the network. In other words, effects of network strength may be negligible when cohesiveness of network is very high or very low. Therefore, for managers of online community services, it is important to make users to stay longer in the network. It can increase the cohesiveness of users and is likely to increase the future usage of the network. An additional finding that may interest managers of Internet community services is that future usage intention is stronger for younger users.

In case of email services, I find no significant effect of network externality factors on future usage intention of the network supporting H6. The result may reflect a unique characteristic of e-mail services. Because most Internet users are already using email services and because an email service is compatible with other email services, they may consider total and local network size to be already satisfactory. Table 2-3 shows that, on average, subjects estimated the size of the total and local network to be 93% and 89%, respectively. The standard deviations for the estimates are very small, too. In addition, most users intend to continue using e-mail services. In summary, the results imply that there is little network externality effects for email services.

2.5 Discussion

Typically, past literature of network externalities focused on effects of total network size on the success of a network. In this study, I investigated effects of three network externality factors on the users' future usage intention of the network services, total network size, local network size and network strength. I showed that local network size and network strength are indeed important network externality factors for some online network services.

For the online messenger service, local network size is found to be a significant determinant for future usage intention of the network. For online community service, local network size and network strength are significant determinants. On the other hand, for chat room services, total network size is the only significant network externality factor. For email services, none of the network externality factors are significant. Being in the mature stage of the life cycle, email services may not have network externality effects any more. Although it is not a network externality factor, satisfaction with the service is also an important determinant of users' future usage intention of the network.

The results suggest some meaningful implications. For online messengers and online communities, local network size is more important than total network size. For example, it will be important to provide easy-to-use buddy lists or easy-to-find-new buddies services for users of online messengers. For managers of online communities, it will be important to provide useful local network services such as helping close friends to form new communities. On the other hand, total network size, emphasized by typical network externalities literature, is truly the most important factor for chat room services. In this case, increasing the size of the network should be the top priority trying to add more and a variety of new members.

Analysis of e-mail services suggest that network externalities effects may disappear when the service is compatible to competing services or reaches the mature stage of life cycle. When most of potential users are already members of such networks, network externality factors may not be a significant determinant of the members' future usage intention of the network services. Thus, depending on the types of networks, managers need to focus on different factors in managing their networks. Managers of Internet services should understand the nature and types of their networks before they make any resource allocation decisions.

There may be several directions for future studies. This study empirically analyzed four Internet services offered in South Korea. Investigation into other online services in other environments may be necessary to generalize the results I have. Similar investigation into off line networks will be also interesting. Network externality is one of many new concepts that have appeared in the digital economy. Incorporating these new concepts into marketing models and comparing them with traditional models will provide opportunities and challenges for research in marketing in the digital economy.

Chapter 3 A Diffusion Model for Products with Indirect Network Externality

Since publication of the diffusion model by Bass (1969), the model was extended to incorporate a variety of characteristics observed in the market. The extensions include incorporating impact of marketing mix variables (e.g., Bass, Krishnan and Jain, 1994; Horsky and Simon, 1983; Kalish 1985; Kamakura and Balasubramanian, 1988; Robinson and Lakhani, 1975; Simon and Sebastian, 1987), repeat purchases (Hahn, Park, Krishnamurthi and Zoltners, 1994; Lilien, Rao and Kalish, 1981; Mahajan, Wind and Sharma, 1983, Rao and Yamada, 1988), and multiproduct interactions (Bayus, 1987; Gupta, Jain and Sawhney, 1999; Islam and Meade, 1997; Johnson and Bhatia, 1997; Norton and Bass, 1987, 1992; Parker and Gatignon, 1994; Peterson and Mahajan, 1978). However, to incorporate the concept of indirect network externality, diffusion models need further extensions.

In markets with indirect network externality, availability or expected availability of hardware products enhances the demand of software products and, at the same time, availability or expected availability of the software products enhances the demand for hardware products. The purpose of this chapter is to develop a model that can forecast sales for markets that show indirect network externality. Specifically, I present a diffusion model that incorporates two way interactive effects between hardware and software products on their demands. The model is easy to apply having the same number of parameters as that of the Bass diffusion model. Also, the model is conceptually reduced to the Bass model when there is no indirect externality effect in the market. It makes us easier to compare the estimated results with those of traditional diffusion models.

A manager in the market with network externality needs to evaluate whether his or her product will achieve a big enough installed base to be successful at an early stage of its product life cycle. I applied the new diffusion model to DVD player market in the United States and in South Korea, and to Digital TV set market in Australia. Utilizing early sales data, I show that the new diffusion model perform well in forecasting both short-term and long-term sales. Especially, the model had smaller forecasting errors for long-term future sales when it was compared to the Bass and NSRL model for the markets characterized by increasing returns.

The remainder of this chapter is organized as follows. I discuss a limitation of multi-product diffusion models with respect to dealing with two way interactions of hardware and software products in the diffusion process. After identifying properties desirable for models of indirect network externality, a new model satisfying such properties is developed. Then, the model is applied to three products in two countries. Finally, I conclude theoretical and managerial implications as well as limitations and possible further extensions of our research.

3.1 Desirable characteristics of models with indirect network externality

The original diffusion model by Bass (1969) was extended to incorporate various characteristics observed in the market. The extensions include incorporating impact of marketing mix variables, repeat purchases, competition and multiproduct interactions (Mahajan *et al.*, 2000). However, to incorporate the concept of indirect network externality, diffusion models need further extensions.

Multiproduct diffusion models in the literature analyze diffusion of more than two different but related products (Bayus, 1987; Gupta *et al.*, 1999; Parker and Gatignon, 1994; Peterson and Mahajan, 1978) or successive generations of a product (Islam and Meade, 1997; Johnson and Bhatia, 1997; Norton and Bass, 1987, 1992). Among them, studies by Peterson and Mahajan (1978), Bayus (1987), and Gupta *et al.* (1999) are of special interest to us because they analyzed diffusion of products having hardware-software relationships. The hardware-software relationship is an inherent characteristic of the indirect network externality.

Peterson and Mahajan (1978) investigated different categories of multiproduct diffusion processes. Four categories were identified based on relationships between two products: independent, complementary, contingent, and substitute relationships. Among the categories, contingent diffusion case considers the hardware-software relationship. For contingent cases, they proposed two related diffusion models, one for hardware and the other for software. However, diffusion of hardware affects the diffusion of software, but not vice versa in the models. Bayus (1987) also developed a similar software diffusion model that depends on sales of hardware products in the market. However, hardware diffusion is not affected by software diffusion in the model.

These models do not incorporate the "chicken and egg problem" between the hardware and software products described by Gupta *et al.* (1999). In the market with indirect network externality, manufacturers of the hardware decide the production quantity considering the availability or expected availability of the software in the market. Similarly, software providers consider how many consumers adopted or would adopt the hardware in the market before they produce the software. Hill (1997) noted the importance of positive feedback of network effects between hardware-software products such as personal computers and computer software products. A model with indirect network externality should incorporate such two way interactions between hard-ware products.

Gupta *et al.* (1999), in predicting the consumer adoption of digital TV, emphasized the importance of considering the two-way interactive relationship. They developed an approach to forecast sales using a discrete choice model and a simulation procedure. However, unlike the Bass diffusion model, their approach is not easy to apply. They utilize in-depth quantitative and qualitative information, such as price and screen size of the digital TV, and quantity and availability of programs for the digital TV in the market.

In the next session, I present a model for forecasting sales of hardware products with indirect network externality. Two essential features can be summarized as follows. (a) The new model incorporates the two way interactive influences of hardware and software products. (b) The model is easy to apply with few sales data points like the Bass model. The ease of application is essential for models to be used in the early periods after the launch of a product.

3.2 Model

To develop a new model with indirect network externality, I extend the following Bass diffusion model.

$$f(t) = [p + qF(t)][1 - F(t)] \tag{3.1}$$

where,

$f(t)$ is density function of time to adoption,

$F(t)$ is cumulative fraction of adopters at time t,

p is coefficient of external influence, and

q is coefficient of internal influence

Consider a DVD player market where there are two way interactions between demand for DVD players (hardware) and that for DVD titles (software). Consider an early stage of the market when adoption rate of the product is low among potential consumers. If potential consumers observe the increasing availability of DVD titles, the observation will enhance the adoption of DVD players. The enhanced adoption of DVD players, in turn, will increase the demand for DVD titles. The traditional diffusion models are likely to underestimate demand for DVD players as well as that for DVD titles because they do not reflect the two way interactions of demands in the models.

In the market with indirect network externality, when consumers purchase a hardware product, they consider the adoption of software as well as that of hardware in the market. Thus, they make their adoption decision based on an adjusted $F(t)$, denoted by $A[F(t)]$, rather than $F(t)$ in the Bass diffusion model as follows:

$$\frac{f(t)}{1-F(t)} = p + qA[F(t)] \tag{3.2}$$

where,

A[F(t)] is adjusted *F(t)* due to indirect network externality.

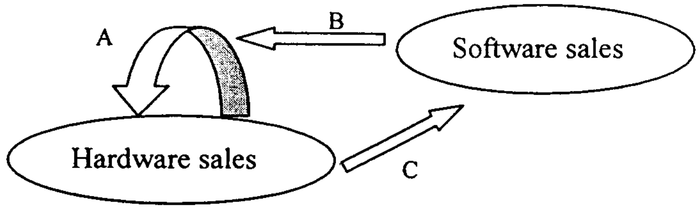
Because adjusted *F(t)* is affected by both the availability of hardware and software products, it is formulated as a general function g{ } as follows:

$$A[F(t)] = g\{F(t), SW(t)\} \tag{3.3}$$

where,

SW(t) is the number of available software at time *t* in the market.

In specifying the function *g*{ }, I incorporate dynamics in the market as shown in Figure 1. Increase in cumulative sales of hardware enhances the sales of hardware for the current period, as shown in *direction A*. Sales of hardware for the current period are also affected by the greater availability of software in the market, as shown as *direction B*. In addition, as sales of hardware products increase, sales of software increase in the market as shown in *direction C* (Gupta *et al.*, 1999; Hill, 1997). I incorporate the effects of direction B and C into the Bass diffusion model.



<Figure 3-1> Proposed Relationship between Hardware and Software Products in the Market with Indirect Network Externality

To incorporate direction B into the diffusion model, function g{ } is specified as a multiplicative function as:

$$g\{F(t), SW(t)\} = F(t) \bullet h(SW(t)) \tag{3.4}$$

where,

h(SW(t)) is a function of *SW(t)*.

The multiplicative specification compactly represent the interaction effects between *F(t)* and *h(SW(t))*. Also, equation (3.4) may be interpreted as adjusting *F(t)* by a function of number of available software products, *h{ }*. Consumers consider availability of the hardware and software together when they adopt the hardware.

I define *h{ }* as:

$$h(SW(t)) = \frac{SW(t)}{SW(t-1)} = 1 + \frac{nsw(t)}{SW(t-1)} \tag{3.5}$$

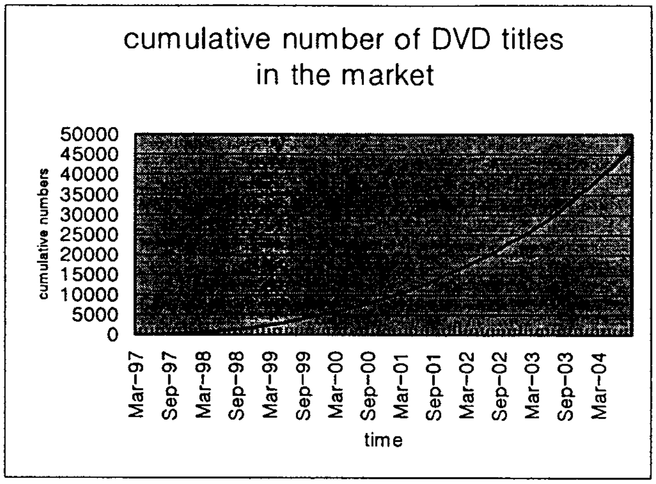
where,

nsw(t) is the number of new software products at time *t* in the market.

By defining *h{ }* as a ratio of number of cumulative software products at time *t* over that at time *(t-1)*, I am assuming that the consumer's adjustment *A[F(t)]* gets greater as the number of software in the market grows faster. Note that, if there is no new software at time *t*, the value of function *h{ }* becomes *1* so that there is no adjustment of *F(t)*. In this case, the model is reduced to the Bass diffusion model. Equation (3.5) is a monotonically increasing function. It reflects that increases in the number of software do not influence the adoption of hardware negatively. Now, equation (3.2) can be written as:

$$\frac{f(t)}{1-F(t)} = p + qF(t)\frac{SW(t)}{SW(t-1)} \tag{3.6}$$

Next, I incorporate direction C of Figure 3.1 into the model. For this purpose, we need to define *SW(t)* as a function of sales of the hardware product. In order to specify the function *SW(t),* I observed the pattern of cumulative number of software in actual DVD market in the United States. The pattern is shown in Figure 3-2.



<Figure 3-2> Cumulative Number of DVD Titles in the U.S. Market

As seen in Figure 3-2, cumulative number of software in the market increases in a convex pattern. As the number of hardware adopters grows in the market, incumbent software providers are likely to produce more new software. Also, potential software providers are more likely to enter the market. Therefore, one unit increase of hardware adopters leads to more than one unit increase in the number of software. To incorporate the pattern, logarithmic, S-shaped, and exponential specifications were considered. I chose to use the exponential specification as it outperformed the other two alternatives as shown in Table 3-1.

Table 3-1. Comparison of Three Alternative Specifications

methods	Adjusted R square	Model significance	
		F value	significant F value
Logarithm	0.0307	1.8862	0.1809
S curve	0.1114	4.5107	0.0430
Exponential	0.5133	30.5267	0.0000

$$SW(t) = \alpha e^{F(t)} \quad (3.7)$$

where,

α is the coefficient of hardware influence on number of software in the market.[1]

Combining equation (3.6) and (3.7), we get:

$$f(t) = [p + qF(t)\frac{\alpha e^{F(t)}}{\alpha e^{F(t-1)}}](1 - F(t)) = [p + qF(t)e^{\{F(t)-F(t-1)\}}](1 - F(t)) \quad (3.8)$$

Note that the model (3.8) and the Bass model use exactly the same data. Also, the two have the same parameters p and q. The only difference is the adjustment of parameters of the model to incorporate the indirect network externality. I will denote these parameters

[1] I first specified the model as $SW(t) = \alpha e^{kF(t)}$. Because there was no substantial improvement in predictive power for various values of k, I decided to use the simple form by setting the parameter k to be 1.

as p', representing p adjusted for indirect network externality, and q', q adjusted for indirect network externality. Still, the interpretation of the adjusted parameters p' and q' are the same as in the Bass model, i.e., the external and internal influence on diffusion, respectively.

To empirically apply the model to a discrete time series data set, I suggest a discrete version of model (3.8) as follows (see Mahajan *et al.* 2000):

$$S(t) = [p' + q'\frac{N(t-1)}{M} e^{I_{INE}\{\frac{N(t-1)}{M} - \frac{N(t-2)}{M}\}}](M - N(t-1)) \qquad (3.9)$$

where,

S(t) is net, i.e., non-cumulative, sales at time *t*,

N(t) is cumulative sales at time *t*,

M is market potential,

p is adjusted *p* due to indirect network externality,

q is adjusted *q* due to indirect network externality, and

I_{INE} is index function such that

$I_{INE}=1$ when indirect network externality exists in the market, and

$I_{INE}=0$ when indirect network externality does not exist in the market.

The model is supposed to use aggregate sales data. Note that, I include an index function, I_{INE}, in the model. The index function lets us easily identify cases where the model is reduced to the Bass model, i.e., where there is no indirect network externality effect in the market.

The new diffusion model has some remarkable characteristics. First, despite the model incorporates a complex dynamics presented in Figure 3-1, it is surprisingly parsimonious. The new model has the same mathematical framework as traditional diffusion models even though it incorporated indirect network externality. Having the equal number of parameters to the Bass diffusion model, it does not require collection of additional information in highly uncertain new product markets, unlike most of extended diffusion models.

Second, the new model is expressed solely as a function of *F(t)* even though it incorporates the effects of the availability of software products. If the model was specified as a function of *SW(t)* as well as that of *F(t)*, researchers will face significant difficulties in applying the model. Collecting software sales data in early stages of emerging markets is one difficulty. The more complicated is converting sales data into normalized adjustment scores that lie in between *0* and *1*. It is very difficult to identify appropriate adjustment scores because they depend on variations and saturation levels of sales. Furthermore, the variations and saturation levels of sales are difficult to estimate being different for different product categories.

Third, the two main parameters p and q have the same conceptual interpretation as those in conventional diffusion models. Because the parameters have the same meaning as other diffusion models, researchers can directly compare the estimates of p?and q with those of p and q obtained in previous diffusion studies. It enables researchers to easily understand the implications of the estimated values.

Fourth, the new model is reduced to the original Bass model when the index function, I_{INE}, is zero. If there is no indirect network externality in the market, the model becomes exactly the Bass model. In other words, the Bass diffusion model is a special case of our proposed model.

The first two characteristics make the new model easy to apply in practice, whereas the last two make researchers easy to interpret the results of the model analysis. In the next section, I empirically apply the new diffusion model to the data of DVD players in the United States and South Korea, and the data of Digital TV sets in Australia. Also, I compare the results with those obtained by applying the Bass model to the same data.

3.3 Empirical Application

Table 3-2 summarizes the data I used. The data of Kimchi refrigerators in South

Korea was included in addition to the three data sets mentioned earlier. Kimchi refrigerator is a refrigerator specifically designed for keeping Kimchi, a Korean traditional food. Recently, the demand for Kimchi refrigerators has grown so fast that it exceeded the demand for general refrigerators. Kimchi refrigerator data set was selected because it is *not* supposed to show any effect of indirect network externality. In the following, I omit the discussion related to the Kimchi refrigerator. The results confirmed our expectation that the new model would not outperform other models in its predictive performance.

Table 3-2. Data Used in This Study

Product	Country	Indirect Network Externality	Period of data
DVD Player	United States	Yes	1997.3~2004.7
DVD Player	South Korea	Yes	2000.1~2003.12
Digital TV Receivers*	Australia	Yes	2002.6~2004.12
Kimchi refrigerator	South Korea	No	1995~2004

* Digital TV receivers include digital television set top box receivers and integrated digital TV sets.

Monthly sales data of DVD players in the United States were collected from The Digital Bits (www.thedigitalbits.com) which is one of the most popular DVD guide websites. The site reveals the monthly sales data of DVD players by courtesy of Consumer Electronics Association.[2] Sales data of DVD player and Kimchi refrigerator in South Korea were collected from Korea National Statistical Office. Sales data of Digital TV receivers in Australia were collected from the DBA (Digital Broadcasting Australia) website.

I compared the forecasting performance of the proposed model with that of the Bass model and non-symmetric responding logistic (NSRL) model. NSRL model was developed by Easingwood *et al.* (1981). It includes a nonuniform influence coefficient to represent the word-of-mouth communication between adopters and nonadopters. By allowing the coefficient of imitation to systematically vary over time, the model can accommodate different diffusion patterns.

The forecasting performance was analyzed in two ways. First, I investigate the short-term forecasting performance by checking errors of the one-step ahead forecasting. Second, I evaluate the performance of forecasting long-term future sales with initial 15 month data. The performance is compared to that of the Bass model and NSRL model. The parameters were estimated using the nonlinear estimation procedure in the SAS package.

Previous diffusion studies recommend researchers to estimate market potential independently of parameters p and q (Mahajan *et al.*, 1990). This study set market potential

[2] LD Combo players are included in these figures, but DVD-ROM drives and DVD-capable PlayStation 2 systems are not. The numbers also include Divx players.

for each product exogenously as follows. First, I selected a product category that is closely related to DVD player and Digital TV set, i.e., TV set. DVD player is a complementary product of TV set. Therefore, I set market potential as the number of households who had TV sets. Then, using the household penetration rate and average number of TV sets per household observed in the TV product, I estimated the final value of market potential for DVD players and Digital TV sets.[3]

Following previous diffusion studies (e.g., Bass *et al.*, 1994; Srinivasan and Mason, 1986; Schmittlein and Mahajan, 1982), I observed errors for one-step ahead forecasting. After fitting the model using data of the first n periods, I forecasted adoption of the (n+1)th period. Then, after re-estimating the model using data of the first (n+1) periods, I forecasted adoption of the (n+2)th period, and so on. Figure 3-3 compares the one-step ahead prediction and actual data. In Table 3-3, the predictive performance of the new model is compared to that of the Bass and NSRL model. Comparisons of MAD (mean absolute deviation), MSE (Mean squared errors), and MAPD (Mean absolute percent deviation) show that predictive errors are substantially reduced for all three data when the new model is compared with the Bass model. The new model shows similar predictive performance for DVD player markets

[3] I relied on Statistical Abstracts of Census Bureau of each country to get the numbers necessary for the estimation. For the sensitivity analysis, I also used four different market potential values (+10%, +20%, -10%, -20%) when estimating the new diffusion model. I found no substantial differences in predicting performance for all the cases.

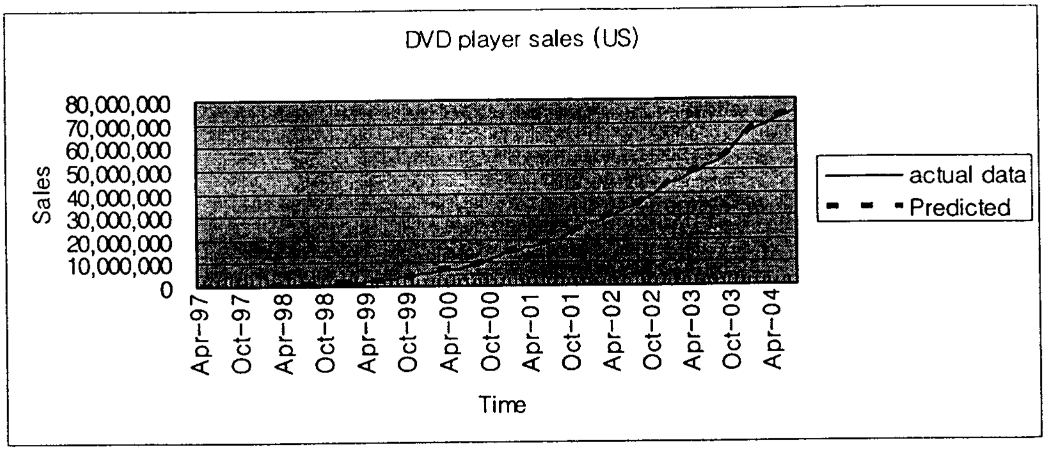
in the U.S. and in Korea when compared to the NSRL model. For Digital TV sets in Australian market, the new model shows better predictive performance than the NSRL model.

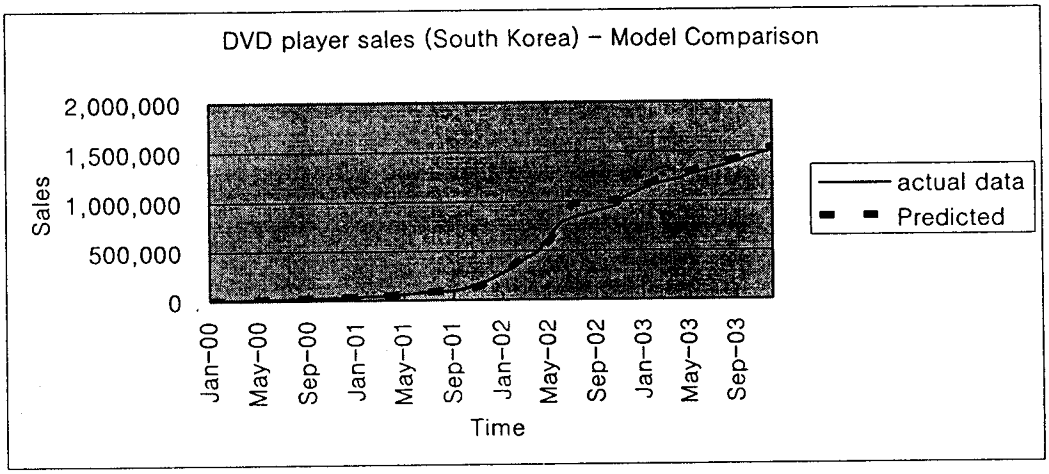
Table 3-3. Model Comparison: One-step Ahead Forecasting

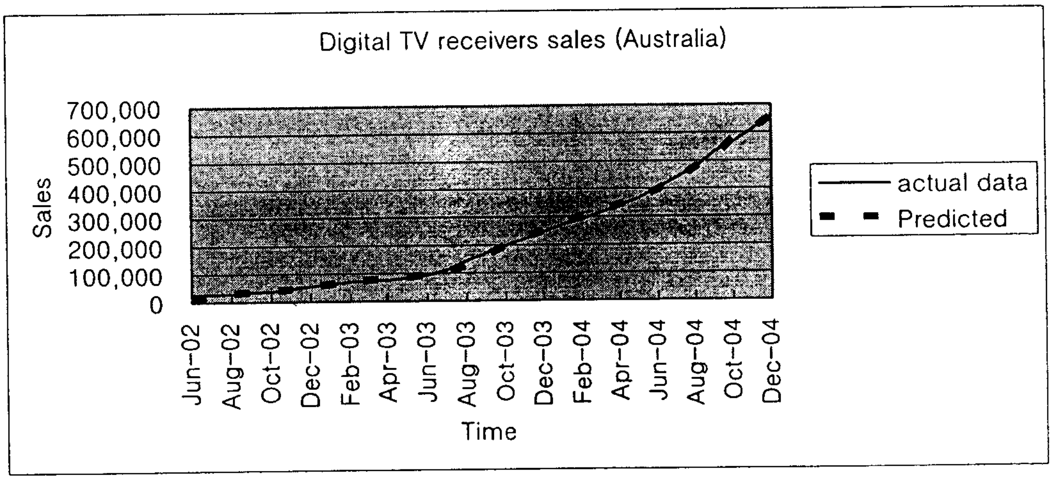
Product	Method	Prediction Error		
		Bass Model	NSRL Model	New Model
DVD Player (United States)	MAD	1,206,546	398,243	428,256
	MSE	3.097E+12	2.91E+11	3.24E+11
	MAPD	4.14%	2.20%	2.26%
DVD Player (South Korea)	MAD	120,729	36,283	37,126
	MSE	2.1752E+10	2.2297E+09	2.3218E+09
	MAPD	11.50%	5.50%	5.35%
Digital TV Receivers (Australia)	MAD	9,271	10,291	5,672
	MSE	1.0850E+08	1.3975E+08	5.5479E+07
	MAPD	2.96%	2.70%	1.77%

MAD: Mean Absolute Deviation / MSE: Mean Squared Errors

MAPD: Mean Absolute Percent Deviation







<Figure 3-3> Comparison of Actual Sales and Fitted Sales (One-step ahead forecast)

Table 3-4. Parameter Estimates of the Bass, NSRL, and New Model

Product	Model	Parameter	Estimate	Approximate Standard Error
DVD Player (United States)	Bass Model	p	0.0001***	<0.0001
		q	0.0412***	0.0052
	NSRL Model	q	0.00152	0.00128
		δ	0.3218***	0.1229
	New Model	p'	0.0001***	<0.0001
		q'	0.0619***	0.0198
DVD Player (South Korea)	Bass Model	p	0.0001***	<0.0001
		q	0.0209**	0.0106
	NSRL Model	q	0.4094	0.7852
		δ	1.1652***	0.3045
	New Model	p'	<0.0001	<0.0001
		q'	0.1241***	0.0327
Digital TV Receivers (Australia)	Bass Model	p	0.0004***	<0.0001
		q	0.0457**	0.0248
	NSRL Model	q	0.4524	0.5351
		δ	1.1053***	0.2271
	New Model	p'	0.0001	0.0002
		q'	0.1205*	0.0814

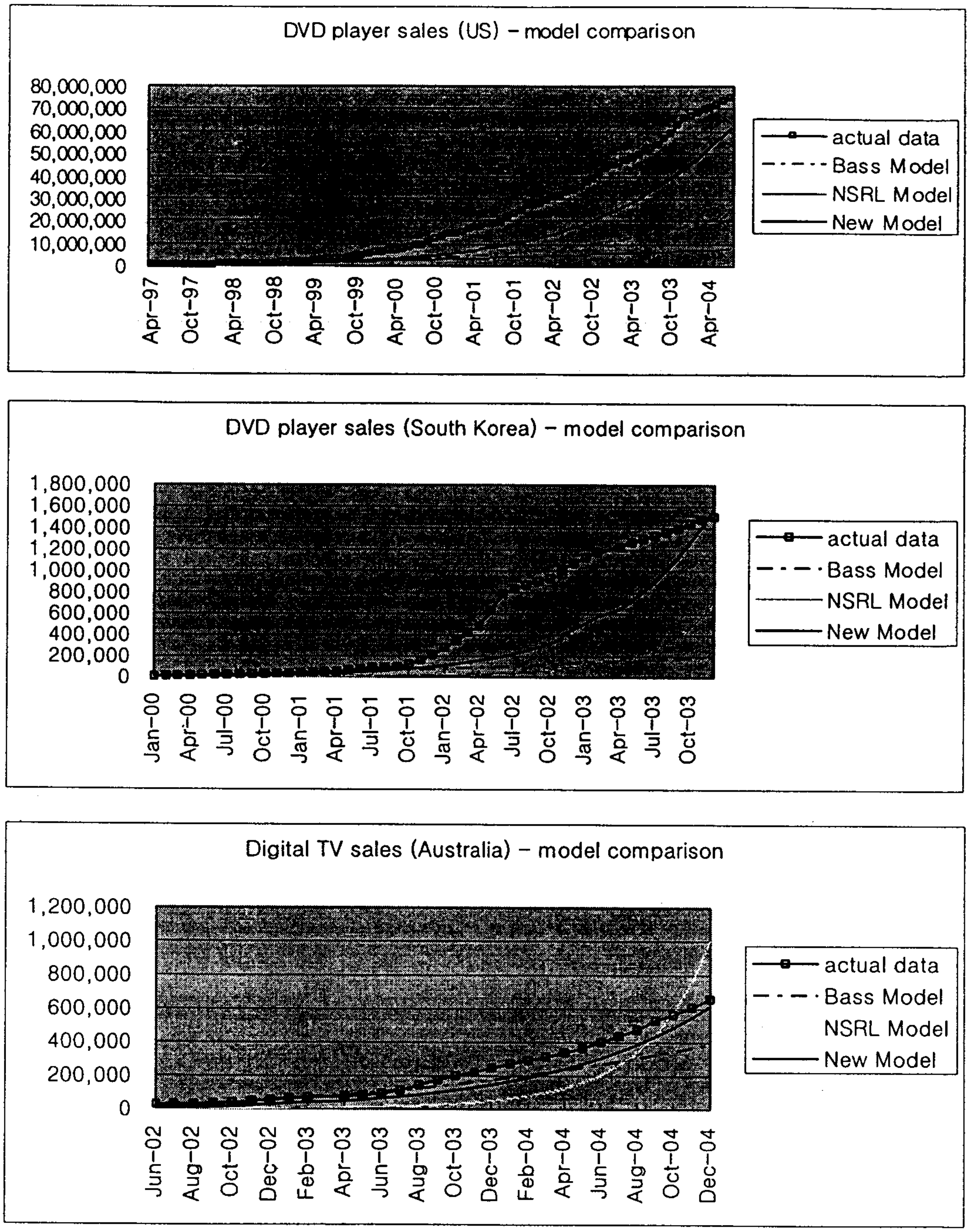
* Coefficients are statistically significant at $\alpha = 0.15$ level

** Coefficients are statistically significant at $\alpha = 0.10$ level

*** Coefficients are statistically significant at $\alpha = 0.01$ level

Next, I forecasted long term sales using initial 15 month data for each product. Then, the predictive errors of the new model were compared to those of the Bass and NSRL model. Compared to the estimates of the Bass model, the estimate of p is smaller than p whereas the estimate of q is greater than q as shown in Table 3-4. The adjusted internal influence (q) is greater because consumer adoptions are affected by the two-way interactive relationships between hardware and software products. The long-range forecasting results of future sales are shown in Figure 3-4.

Figure 3-4 shows that the Bass model underestimates the future sales for all three products as it does not explicitly consider the indirect network externality effect. Also, the NSRL model underestimates the future sales of DVD players in the U.S. and South Korean markets. In case of the Digital TV set in Australian market, the NSRL model overestimates the future sales. The new diffusion model makes forecasts long-term sales better for all three products. The forecast of DVD player sales in the US market for July 2004 is very close to the actual sales although the forecast is made with the data for about 6 years ago. The new diffusion model decreased the prediction error by about 50 million DVD players compared to that of the Bass model. Table 3-5 summarizes the MAD, MSE, and MAPD for the Bass model, NSRL model and the new model for the three products.



<Figure 3-4> Comparison of the Forecasting Results of Bass model, NSRL model and New model (Multi-step ahead forecast)

In the long term sales forecast, the new model reduced forecasting errors by 44.15% and 52.74% on average compared to the Bass model and NSRL model, respectively.

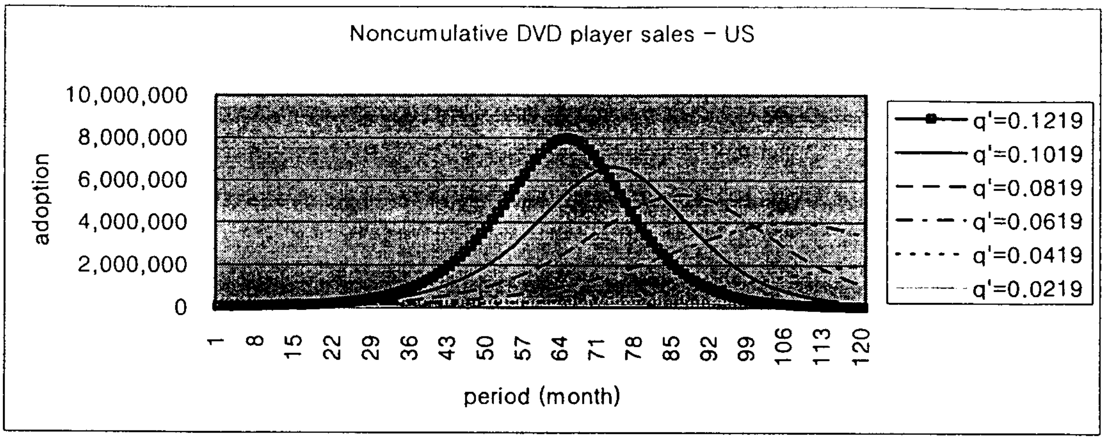
Table 3-5. Model Comparison: Multi-step Ahead Forecasting

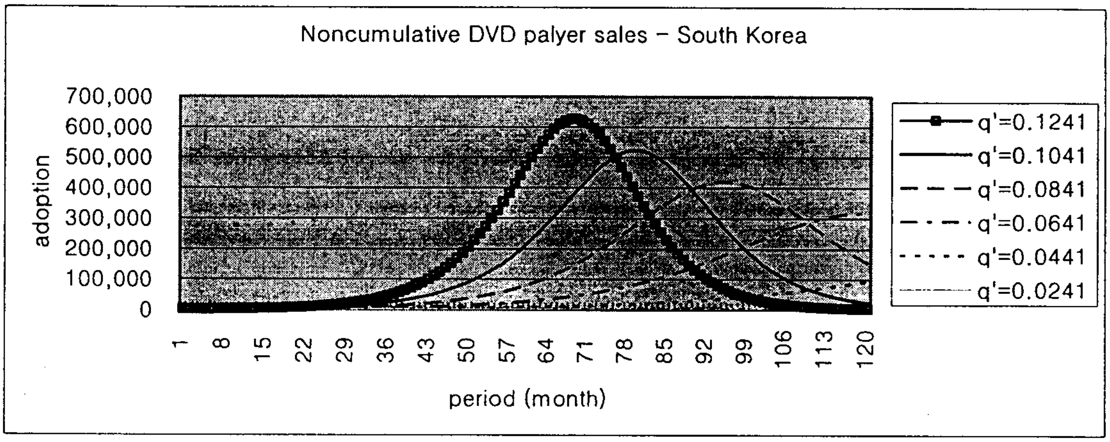
Product	Method	Prediction Error		
		Bass Model	**NSRL Model**	**New Model**
DVD Player (United States)	MAD	1.9162E+07	2.2730E+07	1.0607E+07
	MSE	6.5266E+14	9.6057E+14	1.6852E+14
	MAPD	64.36%	72.63%	43.05%
DVD Player (South Korea)	MAD	7.8489E+05	7.5414E+05	3.9791E+05
	MSE	7.7051E+11	6.6633E+11	2.0348E+11
	MAPD	82.01%	86.19%	49.39%
Digital TV Receivers (Australia)	MAD	1.3098E+05	1.7739E+05	87,648
	MSE	2.1960E+10	3.5945E+10	7.9572E+09
	MAPD	32.31%	54.81%	27.48%

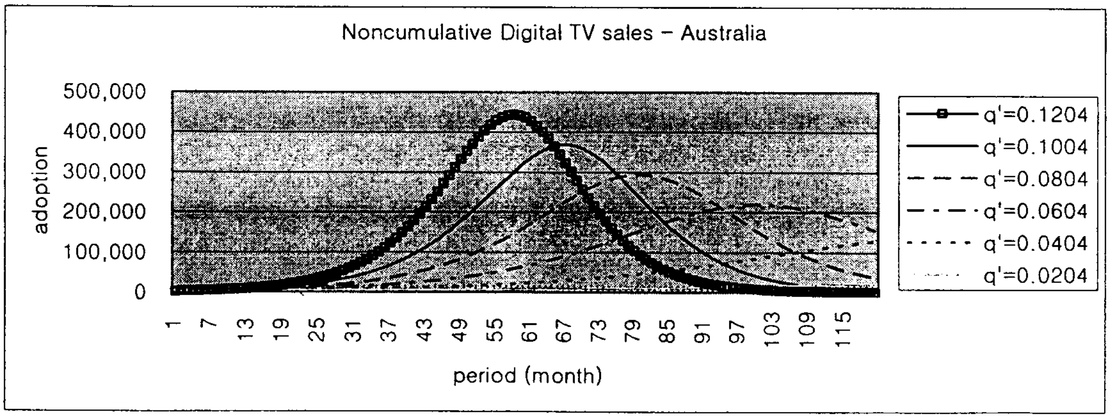
MAD: Mean Absolute Deviation

MSE: Mean Squared Errors

MAPD: Mean Absolute Percent Deviation







<Figure 3-5> Simulation Analysis Based on the Size of the Estimate of q?

One important piece of information for marketers of products characterized by network externality is whether or not the product will get enough installed base to be successful. Although our model does not suggest a direct criterion for predicting the bifurcation, some diagnostic insights can be obtained investigating simulation results as shown in Figure 3-5. For the three products, I investigated how future sales are affected by values of parameter q' in equation (3.9). All three products did not reach their sales peaks in 10 years if the value of q' is smaller than 0.04. Investigating the value for various available products with network externality, marketers will be able to develop a norm to evaluate how probable their product will be successful.

3.4 Discussion

The complex interactions between hardware and software products make demand forecasting more difficult for new high technology products. The more difficult it is to make forecasting, the more important is to rely on appropriate models. Many critical decisions of marketing managers such as timing of investment depend on outcomes of forecasting. Marketing models that incorporate appropriate dynamics in such uncertain markets can help managers predict their future demands with reduced errors.

In this study, I developed a new diffusion model that incorporates one of key concepts in the new digital economy, i.e., indirect network externality. It keeps the simple mathematical form of basic diffusion models although it incorporates a complex phenomenon of indirect network externality. I make it clear that the Bass model is a special case of the new model when there is no indirect network externality in the market. The model, simple it may be, is based on a logical model of dynamics observed in markets with indirect network externality.

The new model is simple enough to be applied with the same number of initial sales data points used by the Bass model. Unlike many other extended diffusion models, the new model has only two parameters making it easy to estimate. The parameters, p and $q?$ are interpreted in the same way as they are in conventional diffusion models. Because they have the same meanings as those in the Bass model, we can compare estimated p' and q' with the estimated results accumulated by a stream of previous diffusion studies. We can compare the results with those analyzed in other product categories or situations. The new model is also parsimonious in that we do not need additional data of software products for its application.

Our application of the model suggests that the new diffusion model can improve both short-term and long-term forecasting performances compared to the Bass model and NSRL model. Especially, when we predict long term future sales, the new model shows a substantial improvement in reducing the prediction errors by incorporating the two way interactive effects of the availability of hardware and software. There can be several directions for future studies. Validity of the new model will be enhanced by applying it to sales data of various products. Because the new model is easy to estimate, it takes little additional efforts to apply the model once data are available. Also, variations of the model may be developed for specific purposes. For example, we may extend the model to incorporate the effects of marketing variables, such as price, in addition to the indirect network externality. Network externality I considered here is just one of many new interesting concepts in the digital economy. There is a rich opportunity for research in marketing that incorporates new concepts appropriate in the digital economy to the traditional marketing models. Such models will be especially helpful to marketers of product categories characterized by increasing returns.

Chapter 4 Conclusion

I have investigated effects of network externality on marketing in the digital economy. In chapter 2, I investigated effects of three network externality factors on the users' future usage intention of the network services, total network size, local network size and network strength. Typically, past literature of network externalities focused on effects of total network size on the success of a network. In this research, I showed that local network size and network strength are indeed important network externality factors for some online network services.

For the online messenger service, local network size is found to be a significant determinant for future usage intention of the network. For online community service, local network size and network strength are significant determinants. On the other hand, for chat room services, total network size is the only significant network externality factor. For email services, none of the network externality factors are significant. Being in the mature stage of the life cycle, email services may not have network externality effects any more. Although it is not a network externality factor, satisfaction with the service is also an important determinant of users' future usage intention of the network.

The results suggest some meaningful implications. For online messengers and online communities, local network size is more important than total network size. For example, it will be important to provide easy-to-use buddy lists or easy-to-find-new buddies services for users of online messengers. For managers of online communities, it will be important to provide useful local network services such as helping close friends to form new communities. On the other hand, total network size, emphasized by typical network externalities literature, is truly the most important factor for chat room services. In this case, increasing the size of the network should be the top priority trying to add more and a variety of new members.

Analysis of e-mail services suggest that network externalities effects may disappear when the service is compatible to competing services or reaches the mature stage of life cycle. When most of potential users are already members of such networks, network externality factors may not be a significant determinant of the members' future usage intention of the network services. Thus, depending on the types of networks, managers need to focus on different factors in managing their networks. Managers of Internet services should understand the nature and types of their networks before the make any resource allocation decisions.

In chapter 3, I developed a new diffusion model that incorporates one of key concepts in the new digital economy, i.e., indirect network externality. The complex interactions between hardware and software products make demand forecasting more difficult for new high technology products. The more difficult it is to make forecasting, the more important is to rely on appropriate models. Many critical decisions of marketing managers such as timing of investment depend on outcomes of forecasting. Marketing models that incorporate appropriate dynamics in such uncertain markets can help managers predict their future demands with reduced errors.

The model keeps the simple mathematical form of basic diffusion models although it incorporates a complex phenomenon of indirect network externality. I make it clear that the Bass model is a special case of the new model when there is no indirect network externality in the market. The model, simple it may be, is based on a logical model of dynamics observed in markets with indirect network externality.

The new model is simple enough to be applied with the same number of initial sales data points used by the Bass model. Unlike many other extended diffusion models, the new model has only two parameters making it easy to estimate. The parameters, p and $q?$ are interpreted in the same way as they are in conventional diffusion models. Because they have the same meanings as those in the Bass model, we can compare estimated p' and q' with the estimated results accumulated by a stream of previous diffusion studies. We can compare the results with those analyzed in other product categories or situations. The new model is also parsimonious in that we do not need additional data of software products for its application.

Our application of the model suggests that the new diffusion model can improve both short-term and long-term forecasting performances compared to the Bass model and NSRL model. Especially, when we predict long term future sales, the new model shows a substantial improvement in reducing the prediction errors by incorporating the two way interactive effects of the availability of hardware and software.

There may be several directions for future studies. In Chapter 2, this study empirically analyzed different characteristics of four Internet services offered in South Korea. Investigation into other online services in other environment may be necessary to generalize the results we have. For example, classifying network structures based on other theoretical approaches could be a good starting point to generalize the results. A similar investigation into offline networks will be also interesting. Methodologically, simulation modeling approaches suggested by the complexity literature may be useful to investigate expanded models and research hypotheses complementing this study. We may also investigate the relationships between conventional marketing concepts such as word-of-mouth effect and network externality factors.

There can be several directions for future studies of chapter 3. Validity of the new model will be enhanced by applying it to sales data of various products. Because the new model is easy to estimate, it takes little additional efforts to apply the model once data are available. Also, variations of the model may be developed for specific purpose. For example, we may apply possible other model specifications when developing software function, SW(t). And we may extend the model to incorporate the effects of marketing variables, such as price, in addition to the indirect network externality. Also, we may try to extend the model to investigate contemporary marketing issues such as market pioneer effects or viral marketing.

Network externality I considered here is just one of many new interesting concepts in the digital economy. There is a rich opportunity for research in marketing that incorporates new concepts appropriate in the digital economy to the traditional marketing models. Such models will be especially helpful to marketers of product categories characterized by increasing returns.

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