Asia Pacific Journal of Information Systems
Vol. 20, No. 1, March 2010

Dynamics of Technology Adoption in Markets Exhibiting Network Effects

Wonchang Hur

The benefit that a consumer derives from the use of a good often depends on the number of other consumers purchasing the same goods or other compatible items. This property, which is known as network externality, is significant in many IT related industries. Over the past few decades, network externalities have been recognized in the context of physical networks such as the telephone and railroad industries. Today, as many products are provided as a form of system that consists of compatible components, the appreciation of network externality is becoming increasingly important.

Network externalities have been extensively studied among economists who have been seeking to explain new phenomena resulting from rapid advancements in ICT (Information and Communication Technology). As a result of these efforts, a new body of theories for 'New Economy' has been proposed. The theoretical bottom-line argument of such theories is that technologies subject to network effects exhibit multiple equilibriums and will finally lock into a monopoly with one standard cornering the entire market. They emphasize that such "tippiness" is a typical characteristic in such networked markets, describing that multiple incompatible technologies rarely coexist and that the switch to a single, leading standard occurs suddenly.

Moreover, it is argued that this standardization process is path dependent, and the ultimate outcome is unpredictable. With incomplete information about other actors' preferences, there can be excess inertia, as consumers only moderately favor the change, and hence are themselves insufficiently motivated to start the bandwagon rolling, but would get on it once it did start to roll. This startup problem can prevent the adoption of any standard at all, even if it is preferred by everyone. Conversely, excess momentum is another possible outcome, for example, if a sponsoring firm uses low prices during early periods of diffusion.

The aim of this paper is to analyze the dynamics of the adoption process in markets exhibiting network effects by focusing on two factors; switching and agent heterogeneity. Switching is an important factor that should be considered in analyzing the adoption process. An agent's switching invokes switching by other adopters, which brings about a positive feedback process that can significantly complicate the adoption

* Assistant Professor, College of Business Administration, Inha University

process. Agent heterogeneity also plays a important role in shaping the early development of the adoption process, which has a significant impact on the later development of the process. The effects of these two factors are analyzed by developing an agent-based simulation model. ABM is a computer-based simulation methodology that can offer many advantages over traditional analytical approaches. The model is designed such that agents have diverse preferences regarding technology and are allowed to switch their previous choice.

The simulation results showed that the adoption processes in a market exhibiting networks effects are significantly affected by the distribution of agents and the occurrence of switching. In particular, it is found that both weak heterogeneity and strong network effects cause agents to start to switch early and this plays a role of expediting the emergence of 'lock-in.' When network effects are strong, agents are easily affected by changes in early market shares. This causes agents to switch earlier and in turn speeds up the market's tipping. The same effect is found in the case of highly homogeneous agents. When agents are highly homogeneous, the market starts to tip toward one technology rapidly, and its choice is not always consistent with the populations' initial inclination. Increased volatility and faster lock-in increase the possibility that the market will reach an unexpected outcome. The primary contribution of this study is the elucidation of the role of parameters characterizing the market in the development of the lock-in process, and identification of conditions where such unexpected outcomes happen.

Keywords : Network Effects, Technology Adoption, Path Dependence, Lock-in, Agent-Based Model

Ⅰ. Introduction

The benefit that a consumer derives from the use of a good often depends on the number of other consumers purchasing the same goods or other compatible items [Leibenstein, 1950; Shapiro and Varian, 1999]. This property, known as demand-side economy of scale, or network externality, has a significant impact on the adoption of new technology. Technology adoption in markets exhibiting network externalities has been extensively studied over the past few decades. Arguably, a common theme among the previous studies is that the market tips suddenly into a single, leading standard and that multiple incompatible technologies rarely coexist [Arthur, 1989; Economides, 1996; Farrel and Saloner, 1985, 1986; Katz and Shapiro, 1985, 1986, 1992, 1994; Liebowitz and Margolis, 1994. 1995]. Compared to the substantial emphasis placed on this property, however, the literature is relatively lacking in deeper analyses on the underlying dynamics that causes such peculiar phenomena to emerge [Liebowitz, 2002; Lee *et al.*, 2003; Lee and Lee, 2006; Weitzel *et al.*, 2006; Roedenbeck and Nothnagel, 2008].

The aim of this paper is, therefore, to analyze the dynamics of the adoption process by focusing on two factors; switching and heterogeneity. Switching is an important factor that should be considered in analyzing the adoption process. In some service industries, It is frequently observed that some early adopters change their selection in favor of other alternatives. For instance, in the mobile service industry, subscribers can freely change their operators without incurring much additional costs. This affects the decision of other agents who have not yet adopted any technology. Furthermore, an agent's switching can invoke switching by other adopters, which brings about cascading of switching. This positive feedback process complicates the adoption process significantly.

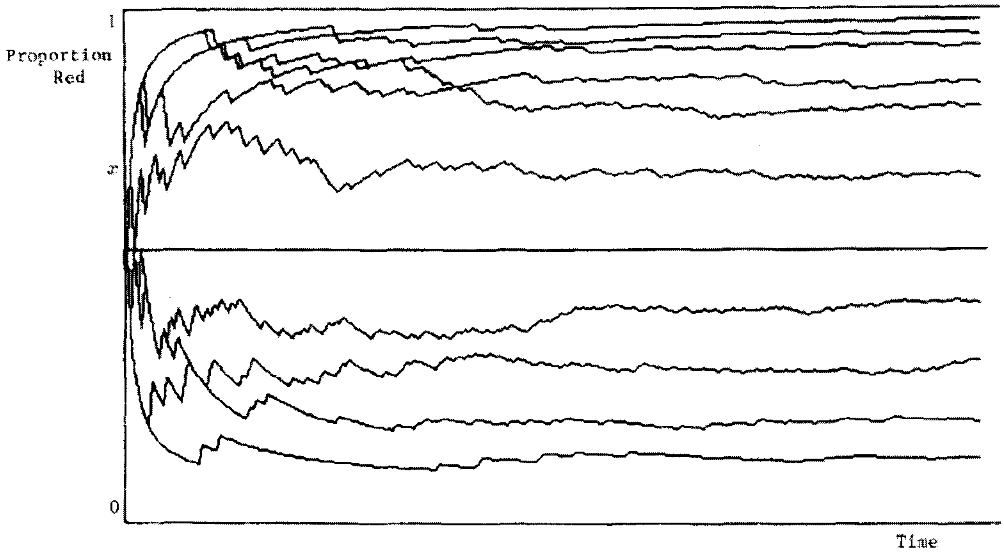
It is also important to examine how heterogeneity of agents will affect the market development. Agent heterogeneity plays a particularly important role in shaping the early development of the market. In a market exhibiting network effects, the early outcome of competition has a significant impact on the later development of the adoption process. During the early stage in which network effects are relatively weak, agents are more likely to make an adoption decision relying solely on their natural inclination. As a result, the dynamics of the adoption process is highly dependent upon the heterogeneity of agents.

To examine the role of these two factors, we built an artificial market by employing an agent-based modeling (ABM) approach. ABM is known as a more appropriate approach in understanding the emergence of macro phenomena as a result of dynamic micro interactions among heterogeneous agents [Schelling, 1978; Tesfatsion, 2002; Gilbert and Troitzsch, 2005; Miller and Page, 2007; Zenobia *et al.*, 2009]. In adoption processes, an agent's adoption and switching generate interactions at a micro level, and the continued accumulation of these interactions leads to the emergence of a particular market outcome. In this regard, the ABM approach is expected to overcome the limitations of existing studies based upon conventional analytical approaches.

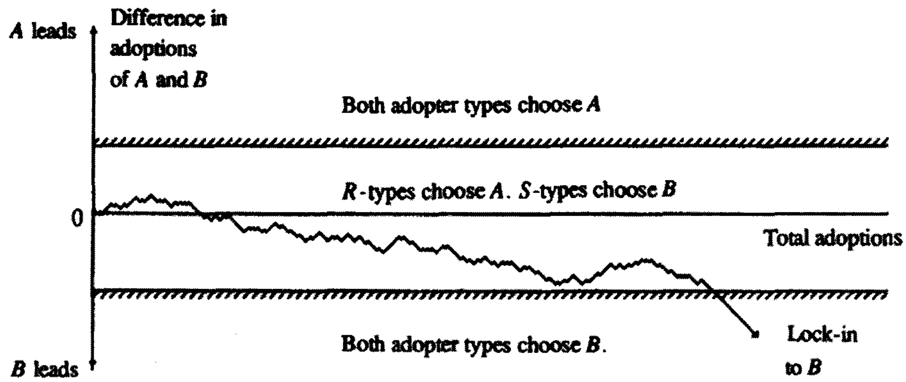
Ⅱ. The path dependent process

Imagine an urn of infinite capacity to which are added balls. Initially, two balls of two different colors, red and white, are placed in the urn. An agent draws one ball randomly from the urn, observes its color, and then places the ball back in the urn with one addition ball of the same color. Polya, who first considered this simple process, found a relatively striking result regarding the outcome of the process. He showed, in his 1931 paper, that the proportion of red balls does tend to have a limit X with probability one, and X is a random variable uniformly distributed between 0 and 1 (see <Figure 1>) [Johnson and Kotz, 1997; Arthur *et al.*, 1987].

Arthur *et al.* focused on the 'path dependence' characteristic in the Polya urn process and applied the concept to technology competition [Arthur and Ermoliev, 1987, Arthur, 1989]. By introducing a simple technology adoption model, he suggested that the adoption of new technology can be a path dependent process when technology is subject to strong network effects. In his model, adopters adopt one of two competing technologies. The adoption decision of an agent is dependent upon its natural inclination for one alternative plus the decisions of past adopters. To simplify the analysis, he assumed that adopters are divided into two distinct separate and homogeneous groups, R and S, based on their fixed natural in-



<Figure 1> a Polya urn Process (Arthur *et al.*, 1987)



<Figure 2> Arthur's lock-in Process (Arthur, 1989)

clinations.[1)] That is, R-agent initially prefers A to B, and S-agent vice versa. In the adoption process, an agent of a randomly chosen type enters the market, chooses the latest version of either technology A or technology B, and uses this version thereafter.

1) Later, Arthur suggested an extension using a continuum of adopters with fixed arbitrary set preferences across two or multiple technologies.

The result of simulating this process, as shown in <Figure 2>, shows that once the difference in adoptions exceeds a certain point, adoptions, thereafter, become locked into one technology regardless of its superiority or inferiority to the other technology. The reason why this 'lock-in' occurs is that the adoption is affected by 'historical events,' or is path dependent [David, 1985; Economides and Himmelberg, 1995; Arthur, 1987, 1989]. That is, the fact that the present adoption is decided based upon the past adoption results inevitably gives rise to a positive feedback process that will eventually lock-out one technology from the market.

Ⅲ. The Market Process with Switching

3.1 The Simulation Model

In order to simulate adoption processes, we built an agent-based computational model. We extend the Arthur's model by considering two factors; agent heterogeneity and switching. In our model, agents adopt one of two competing technologies based upon their utility. The utility of a technology is determined by the agents' natural inclination and the number of its current adopters (see <Table 1>). The coefficient a is used to control the strength of network effects. Unlike Arthur's model, we assumed that agents are heterogeneous in terms of their technological preferences [Roedenback and Nothnagel, 2008]. To model this, instead of using a fixed value, we defined a random variable r as the difference of r_A and r_B, and it is assumed to follow a normal distribution with mean μ and variance σ. The mean of r indicates the degree to which agents are biased toward one particular technology. In the model, if μ is positive (or negative), it means that agents on average are more inclined to technology A (B). The variance σ represents the heterogeneity of agents' inclination to technology. The distribution of agents, which is determined by μ and σ, is an important factor characterizing an adoption process.

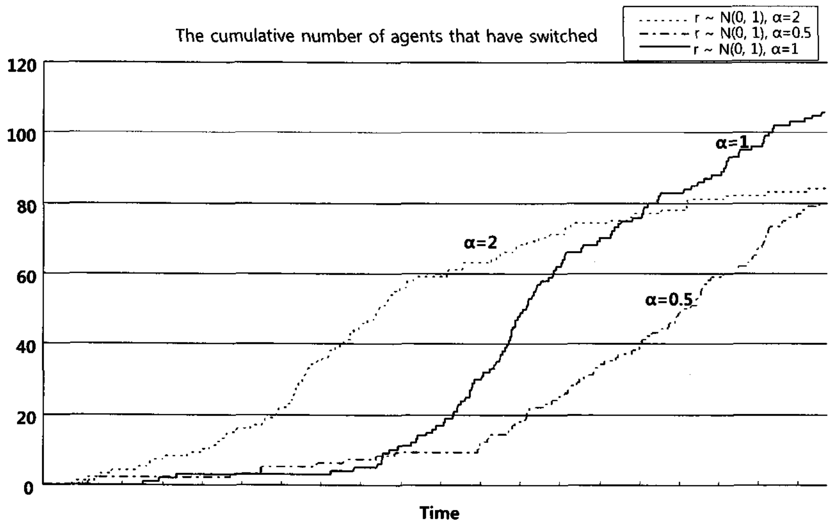
<Table 1> Utility function for experiments

	Technology A	Technology B
Adopters' utility	$r_A + a \times n_A$	$r_B + a \times n_B$

Another important feature of our model is that agents are allowed to change their current adoptions. As the number of adopters increases over time, the utility of the technology increases accordingly. Therefore, for some adopters, the time may come when the utility of the adopted technology becomes smaller than that of the other technology. In our model, one of such adopters is randomly selected each time and switches to the other alternative. Notice that while adoption takes place following a Poisson process, switching occurs whenever there are agents who so desire. Therefore, the speed of market development is affected by the inter-adoption time (λ) and the number of simultaneous switches allowed in the model. Various values for these parameters are tried in the experiments, and the values that can effectively demonstrate the findings of the analysis are chosen. We used 3 for λ and assumed that only one agent can switch each time.

3.2 The results

Once switching is allowed, an adoption process becomes dependent upon the manner in which switching occurs during the process. The patterns of switching are affected by the market traits such as the strength of network effects or the distribution of agents' natural inclinations. In order to investigate this relationship, we first examined how network effects affect the switching patterns. <Figure 3>

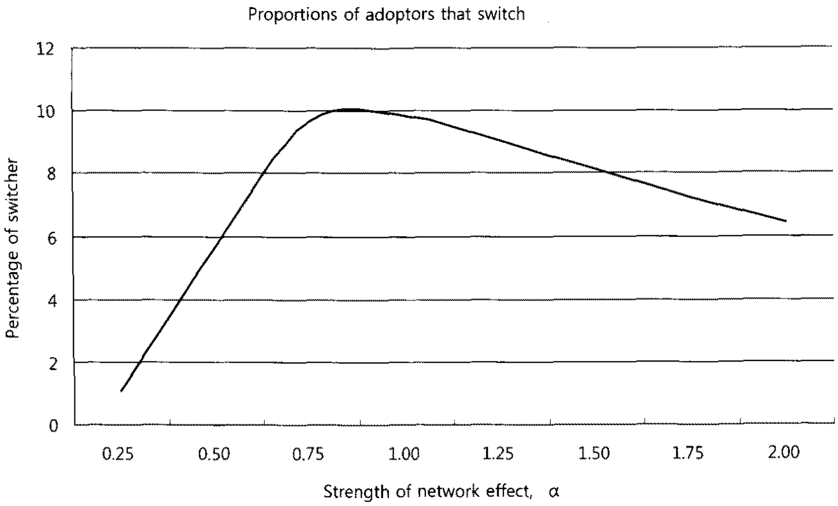


<Figure 3> The Cumulative Number of Agents that have Switch for Various Values of α

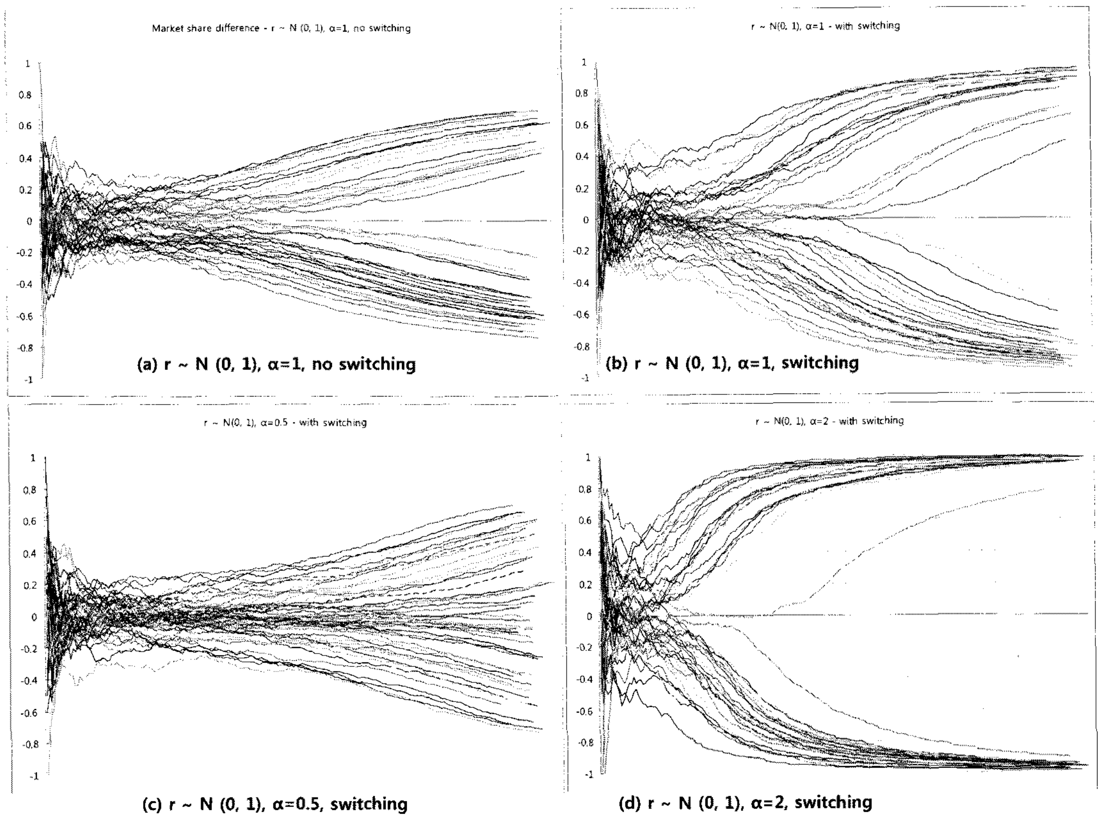
shows when agents start to switch for three different adoption processes. For each of the processes, a simulation is conducted until there are 1,000 adopters in the market. From the graph, it is observed that agents start to switch earlier as the market exhibits stronger network effects. The reason is relatively intuitive. When α is large, it plays a role of amplifying small fluctuations of market share and causes a sufficient change in utility, which can induce agents to switch. Similarly, if network effects are weak, agents would not switch until there are sufficient numbers of adopters in the market.

Notably, a larger α does not always mean that the more agents switch in the process. Rather, as α goes beyond a certain point, the number of switching agents starts to decreases. In <Figure 4>, we can see that the proportion of agents that have switched has an inverted-U type relationship with α. The graph is obtained by averaging the results of 10,000 simulation runs. In the figure, when α is below 1, the number of switching agents increases proportionally to α. However, when α becomes larger than 1, the number of switching agents decreases even though α increases. This is because when agents start to switch early, the market consequently tips rapidly. This rapid stabilization of the market plays a role of reducing the total occurrences of switching.

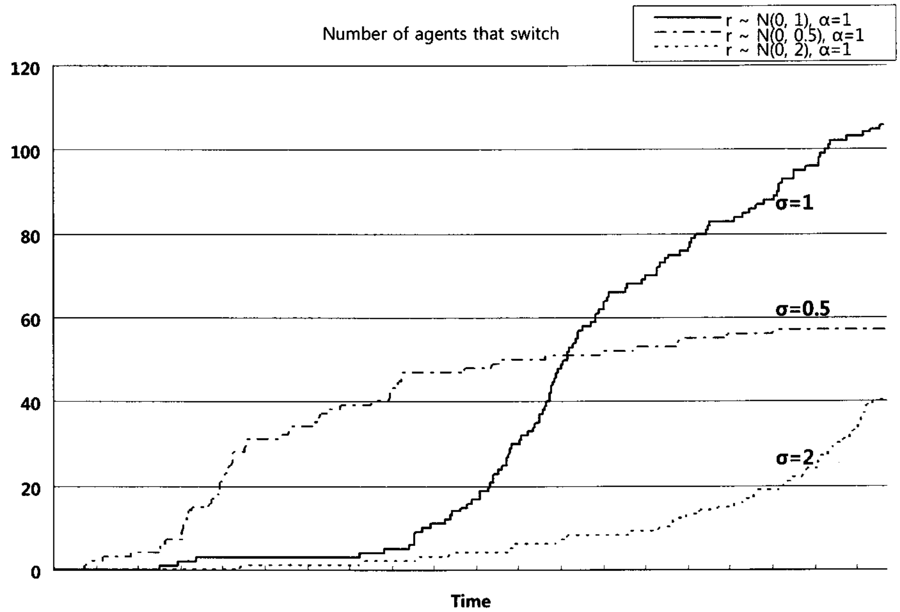
Based upon these findings, we examined how the original adoption process (without switching) is affected when switching is allowed for. <Figure 5> shows the development of the market share difference between the two competing technologies. Graph (a) in the figure shows the development of a typical lock-in process. By comparing (a) and (b), we can see that the market share starts to fluctuate earlier and in a wider range when switching is allowed for. This increased volatility in the early stage has a significant effect on the further development



<Figure 4> Network Effect and Switching Frequency



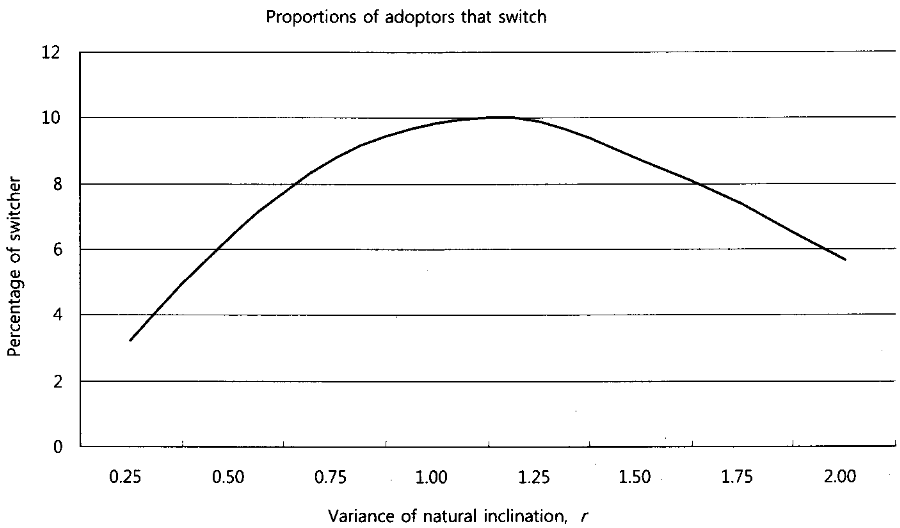
<Figure 5> Adoption Processes Depending Upon the Strength of Network Effects



<Figure 6> The Cumulative Number of Agents that have Switched for Various Values of α

of the market. When the variation of the market share becomes larger, it is more likely that the market share of one technology will reach a lock-in point relatively earlier. This implies that switching plays a role of expediting the emergence of lock-in and thus causes the market to tip faster.

As shown in (c) and (d) in <Figure 5>, it is



<Figure 7> Variance of Natural Inclination and Switching Frequency

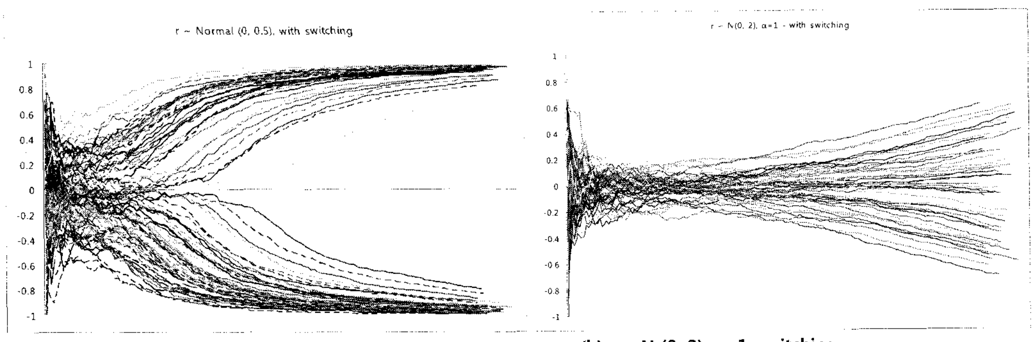
found that network effects, which cause agents to switch early, play a role of speeding up the lock-in process accordingly. When α is 2, even though the total number of switching agents is small, the market starts to tip early and very rapidly. From this, it can be seen that the speed of the market's tipping is more associated with *when* agents start to switch than *how many* agents actually have switched.

Similar results were obtained regarding the variance of agents' natural inclination. At this time, we fixed α at 1, and conducted simulations by changing σ. <Figure 6> shows that agents start to switch earlier as the variance becomes lower. Low variance means that populations are less diversified in terms of their preferences regarding technology. In this case, many agents can be induced to switch by even small changes in market share. In a similar vein, when variance becomes higher, then there are more agents that rely on their natural inclination and they are not affected by early variation of market share.

As mentioned before, the timing of switching is not linearly correlated with the frequency of switching. The same principle applies to this case. As shown in <Figure 7>, it is found that variance σ also has an inverted-U type relationship with the proportion of switching agents. When variance is high, agents start to switch later and the number of switching agents becomes small. On the other hand, when variance is low, although agents start to switch early, the total number of switching agents remains small. As noted before, this is because the market rapidly falls into a locked- in state, in which agents no longer switch.

As shown in (a) and (b) in <Figure 8>, low variance, as in the case of strong network effects, makes the market process more volatile and thus causes it to tip early. When variance is low, agents start to switch earlier. This makes the market tip faster regardless of the amount of switching. From this, we can see that both the homogeneity of agents and the strength of network effects have significant effects on expediting the occurrence of switching, and, thereby, the emergence of the market's tipping.

In addition to the experiments presented thus far, we examined how switching affects the final outcome of an adoption process. To do this, it is supposed that, μ, the mean of r is not zero (μ = 1). That is, agents are more inclined to technology A. In this case, in a market with no



(a) r ~ N (0, 0.5), α=1, switching (b) r ~ N (0, 2), α=1, switching

<Figure 8> Agent Heterogeneity and the Market Process

network effects, market processes would become deterministic provided that adoption takes places for a sufficient amount of time. However, as network effects become stronger, there is a chance that the less preferable technology will win a larger market share. <Table 2> presents the experimental results. As seen in the table, when α is 0.2, the probability that B becomes the market leader is only 6.18%. However, when α is increased to 5, the probability becomes more than 30%. That is, for more than 3 out of 10 cases, technology B becomes a market leader even though more agents are initially inclined to technology B. The probability is slightly larger when switching is allowed for. This result suggest that increased volatility of the market speeds up the lock-in process, and this increases the possibility that the market will make a different choice from the individual's initial inclination.

Ⅳ. Conclusion

In this study, we showed that the adoption processes in a market exhibiting networks effects are significantly affected by the distribution of agents and the occurrence of switching. In particular, it is found that switching plays a role of expediting the emergence of lock-in and thus causes the market to tip faster. This result is paradoxical because it is usually believed that consumers can avoid 'lock-in' if they can switch freely. The results also suggest that both strong network effects and high homogeneity of agents' preference expedite the occurrence of switching and the emergence of tipping. When network effects are strong, agents are easily affected by changes in early market shares. This causes agents to switch earlier and, in turn, speeds up the market's tipping. The same effect is found in the case of highly homogeneous agents. When agents are highly homogeneous, the market starts to tip toward one technology rapidly, and its choice is not always consistent with the populations' initial inclination. Increased volatility and faster lock-in increase the possibility that the market will reach an unexpected outcome.

The lock-in process has received much attention due to its clear implications on market failure in highly networked markets. However, the literature does not provide sufficient evidences regarding the conditions under which the market process will be locked-in or the significant factors that hasten the emergence of lock-in. The primary contribution of this study includes the elucidation of the role of parameters characterizing the market in the development of the lock-in process and the identification of the conditions where such unexpected outcomes arise. Our study suggests that the lock-in process can develop, but it emerges when the market satisfies such conditions as strong network effects, high homogeneity of consumer preferences, and low switching cost. If network effects are relatively weaker than

<Table 2> Probability that Technology B has a Larger Market Share (r~N(1, 1), 10,000 runs)

	α = 0.2	α = 0.5	α = 1	α = 1.5	α = 2	α = 2.5	α = 3	α = 5
No switching	6.18%	9.38%	15.22%	19.46%	22.80%	25.42%	26.79%	31.56%
Switching	6.02%	9.51%	16.79%	21.39%	24.12%	27.33%	28.16%	33.20%

expected, or agents' inherent preferences are highly heterogeneous, or agents cannot switch easily, then the lock-in process may not develop.

The simulation results offer some strategic implications for firms. First, firms need to understand how much customers' decision will be affected by others' adoption. The exact assessment of the strength of network effects is vital for firms to prepare more effective strategies to establish a strong customer base. Second, it is also important for firms to have complete information about potential adopters' preferences. Depending on the distribution of potential adopters' preferences, the outcomes of adoption processes can be different. As suggested by the simulation results, when potential adopters are more homogeneous in terms of their preference to technology, it is more likely that the market tips suddenly into a single technology. This is because the potential adopters are likely to behave more collectively when they have more similar preferences with each other. This excess momentum due to collective behavior is a possible outcome, particularly when a sponsoring firm uses low prices during early periods of diffusion (Farrell and Saloner, 1986).

Although this research produced some important findings, its limitations call for further studies. First of all, we did not consider the price of technology, which can be an important variable affecting an agent's natural inclination to technology. In our model, we assumed natural inclination is given exogenously and does not change throughout the adoption process. However, in reality, pricing can be an important strategic tool for firms to allure more customers, and it is possible that the agent's natural inclination itself changes according to various pricing strategies. Second, it should be noted that the assumptions of a firm's behavior on which our research is founded have not yet been completely supported by empirical researches. Although there has been a wealth of theoretical arguments and discussions, it has been also claimed that there is a lack of empirical supports for them. Although network effects are pervasive in the economy, we see scant evidence of the existence of network externalities. There is really very little detailed and careful empirical support for the view that there are important network externalities that remain uninternalized. Although it has been pointed out that this might be due to limitations of the data availability, it is obvious that this field requires further empirical studies.

〈References〉

[1] Arthur, W.B., "Competing technologies, increasing returns, and lock-in by historical events," *Economic Journal*, Vol. 99, No. 394, 1989, pp. 116-131.

[2] Arthur, W.B., "Increasing Returns and the Two Worlds of Business," *Harvard Business Review*, Vol. 74, No. 4, 1996, pp. 100-109.

[3] Arthur, W.B., Ermoliev, Y.M., and Kaniovski, Y.M., "Path Dependent Processes and the Emergence of a Macro Structure," *European Journal of Operational Research*, Vol. 30, 1987, pp. 294-303.

[4] David, P.A., "Clio and the Economics of QWERTY," *American Economic Review*, Vol.

75, No. 2, 1985, pp. 332-337.

[5] Economides, N. and Himmelberg, C., Critical Mass and Network Size with Application to the US Fax Market. Mimeo, Stern School of Business at New York University, NY, 1995.

[6] Economides, N., "The economics of networks," *International Journal of Industrial Organization*, Vol. 14, No. 6, 1996, pp. 673-699.

[7] Farrell, J. and Saloner, G., "Installed Base and Compatibility: Innovation, Product Preannouncements, and Predation," *American Economic Review*, Vol. 76, No. 5, 1986, pp. 940-955.

[8] Farrell, J. and Saloner, G., "Standardization, Compatibility, and Innovation," *Rand Journal of Economics*, Vol. 16, No. 1, 1985, pp. 70-83.

[9] Gilbert, N., Troitzsch, K.G., Simulation for the Social Scientist: Second ed. Open University Press, New York, NY, 2005.

[10] Johnson, N., Kotz, S., Urn Models and their Application. John Wiley and Sons, New York, NY, 1977.

[11] Katz, M.L. and Shapiro, C., "Network Externality, Competition and Compatibility," *American Economic Review*, Vol. 75, No. 3, 1985, pp. 424-440.

[12] Katz, M.L. and Shapiro, C., "Product Introduction with Network Externalities," *Journal of Industrial Economics*, Vol. 40, No. 1, 1992, pp. 55-83.

[13] Katz, M.L. and Shapiro, C., "Systems Competition and Network Effects," *Journal of Economic Perspectives*, Vol. 8, 1994, pp. 93-93.

[14] Katz, M.L. and Shapiro, C., "Technology Adoption in the Presence of Network Externalities," *The Journal of Political Economy*, Vol. 94, No. 4, 1986, pp. 822-841.

[15] Leibenstein, H., "Bandwagon, Snob, and Veblen Effects in the Theory of Consumers' Demand," *Quarterly Journal of Economics*, Vol. 64, No. 2, 1950, pp. 183-207.

[16] Lee, E. and Lee, J., "Reconsideration of the Winner-Take-All Hypothesis: Complex Networks and Local Bias," *Management Science*, Vol. 52, No. 12, 2006, pp. 1838-1848.

[17] Lee, J., Lee, J., and Lee, H., "Exploration and Exploitation in the Presence of Network Externalities," *Management Science*, Vol. 49, No. 4, 2003, pp. 553-570.

[18] Liebowitz, S.J. and Margolis, S.E., "Network Externality: An Uncommon Tragedy," *The Journal of Economic Perspectives*, Vol. 8, No. 2, 1994, pp. 133-150.

[19] Liebowitz, S.J. and Margolis, S.E., "Path Dependence, Lock-in, and History," *Journal of Law and Economics*, Vol. 22, No. 1, 1995, pp. 1-26.

[20] Liebowitz, S.J., Re-Thinking the Network Economy: The True Forces That Drive the Digital Marketplace, AMACOM, a Division of American Management Association, New York, NY, 2002.

[21] Miller, J.H. and Page, S.E, Complex Adaptive Systems: An Introduction to Computational Models of Social Life. Second ed. Princeton University Press, New Jersey, 2007.

[22] Roedenbeck, M.R.H. and Nothnagel, B., "Rethinking Lock-in and Locking: Adopters Facing Network Effects," *Journal of Artificial Societies and Social Simulation*, Vol. 11, No. 14, 2008, http://jasss.soc.surrey.ac.uk/11/1/4.html,

[23] Schelling, T.C., Micromotives and macrobehavior, W.W. Norton and Co., New York, NY, 1978.

[24] Shapiro, C. and Varian, H.R., Information Rules: A Strategic Guide to the Network

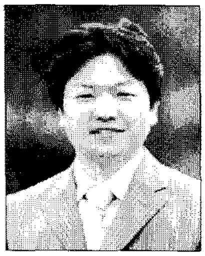
Economy, Harvard Business School Press, Boston, 1999.

[25] Tesfatsion, L., "Agent-Based Computational Economics: Growing Economies from the Bottom Up," *Artificial Life*, Vol. 8, No. 1, 2002, pp. 55-82.

[26] Weitzel, T., Beimborn, D., and Konig, W.A., "Unified Economic Model of Standard Diffusion: The Impact of Standardization Cost, Network Effects, and Network Topology," *MIS Quarterly*, Vol. 30, No. 1, 2006, pp. 489-514.

[27] Zenobia, B., Weber, C., and Daim, T., "Artificial Markets: A Review and Assessment of a New Venue for Innovation Research," *Technovation*, Vol. 29, No. 4, 2009, pp. 338-350.

◆ About the Authors ◆



Wonchang Hur

Wonchang Hur is an assistant professor of MIS in College of Business Administration at Inha University, Incheon, Korea. His research interests include business process management, economics of IT, and technological innovation and entrepreneurship. His research has been published in a number of journals, including Communications of the ACM, Technological Forecasting and Social Change, Concurrent Engineering, IEEE internet computing, Computers in Industry, and Journal of Digital Imaging.