

# Reconsideration of the Winner-Take-All Hypothesis: Complex Networks and Local Bias

Eocman Lee, Jeho Lee

Graduate School of Management, Korea Advanced Institute of Science and Technology, 207-43 Cheongryangri-dong,  
Dongdaemun-gu, Seoul 190-012, Korea {makeyourich@gmail.com, jlee@kgsm.kaist.ac.kr}

Jongseok Lee

Department of Business Administration, Hallym University, 39 Hallymdaehak-gil, Chunchon, Kangwon-do 200-702, Korea,  
ljs@kgsm.kaist.ac.kr

The literature on network effects has popularized a hypothesis that competition between incompatible technologies results in the “winner-take-all” outcome. For the survival of the firm in this sort of competition, the installed base has been emphasized. We argue that the validity of this hypothesis depends on how customers interact with one another (e.g., if they exchange advice or files). In some interaction networks, customers influenced by their acquaintances may adopt a lagging technology even when a lead technology has built a large installed base. The presence of such a local bias facilitates the persistence of incompatibilities. When local bias cannot be sustained in other interaction networks, one technology corners the market. Our study suggests that overemphasizing the installed base, while ignoring network structure, could mislead practitioners.

*Key words:* network externalities; network; increasing returns; technology; complexity

*History:* Accepted by Dan Levinthal, business strategy; received January 7, 2002. This paper was with the authors 28 months for 3 revisions.

## 1. Introduction

The literature on network effects has had considerable impact on managerial practices recently (Farrell and Klemperer 2001). It has indicated that, in a market that demonstrates network effects, a firm or technology that gets ahead tends to increase its market share, cornering the market over time (e.g., Arthur 1989, Shapiro and Varian 1999); a firm or technology that lags behind is likely to lose its market share. It may even be driven out eventually.

This extreme possibility has been called the “winner-take-all” hypothesis in the popular literature (Arthur 1996, Kelly 1998, Shapiro and Varian 1999). This literature suggests that the winner-take-all markets would be more common in the New Economy, where networks play an increasing role in shaping customer choices and technology competition. Practitioners interpreted the hypothesis and often took action in the form of implementing the “get-big-fast” strategy. In the midst of the late 1990s Internet bubble, dot-com companies rushed to build large installed bases ahead of the competition in emerging markets (Liebowitz 2002). Some Internet start-ups even gave away free PCs just to attract customers. Frequently, the size of an installed base was used for valuation of an Internet start-up.

However, the unconditional, winner-take-all hypothesis has baffled many practitioners, as incompatible

technologies often persist (Shapiro and Varian 1999). In such a situation, the implementation of the get-big-fast strategy by all players could lead to a costly war with no clear benefit. Obviously the field could benefit from boundary conditions regarding when the hypothesis will work and when it will not. The objective of this paper is to take a step toward identifying these conditions.

Much of the prior work on network effects has emphasized an installed base (e.g., Katz and Shapiro 1985, 1992; Farrell and Saloner 1986; Arthur 1989). The typical assumption has been that customers value the general connectivity of an entire network.<sup>1</sup> That is, customer benefits of adopting a product depend on how many other customers in the market also use this product. This global network effects assumption may not be a bad approximation when compatible complements indirectly reinforce the benefits of a given product; these benefits are called *indirect*

<sup>1</sup> Farrell and Klemperer (2001) thoroughly reviewed the research on network effects. Their 90-page review contains no other assumption than this one on global effect. However, there were some exceptions. Cowan and Miller (1998), for example, examined the effects of local networks on equilibrium outcomes. In the analysis of bandwagon effects, Abrahamson and Rosenkopf (1997) also considered the effect of network structure on diffusion of a single product. Lee and Song (2003) studied whether a new incompatible technology can challenge an existing technology in diverse network topologies.

network effects (Katz and Shapiro 1985). In the markets for VCRs and CD players, for example, hardware products alone offer little value to customers. The benefits of using them come mainly from the availability of diverse complements such as prerecorded tapes or CDs. The diversity of complements is largely affected by the number of units sold for each hardware platform (Katz and Shapiro 1986, Langlois and Robertson 1992), because independent producers of complements prefer to develop more prerecorded tapes or CDs for a hardware platform with a larger installed base. In these sorts of markets, we do not doubt that control over an installed base is often crucial for waging a standards war (Farrell and Saloner 1986, Shapiro and Varian 1999).

However, we also believe that a customer's selection of a technology is sometimes influenced more by the opinions and choices of his or her acquaintances than by the size of an installed base. Exchanging files or advice with others is often a key source of benefits for complex hardware or software. Such benefits are called *direct* network effects (Katz and Shapiro 1985) and are realized through interactions among customers. In sharing experiences or files with others, a customer is more likely to contact his or her acquaintances (e.g., coworkers or friends) than the majority of unknown others in a network of all previous adopters. Usually, the customer maintains relationships with a small number of acquaintances. It is quite possible that some of these acquaintances will adopt a lagging technology even when a lead technology has built a large installed base. This situation is called *local bias*. Such a local bias may, over time, act as a brake on the winner-take-all process. A lead technology may then find the winner-take-all process limited, leaving room for smaller rivals to survive.

Consider an example of local bias. In the 1990s, MCI, a small long-distance carrier, initiated a marketing campaign called "Calling Circle" to foster local bias deliberately. If a customer built a friends-and-family network using MCI's service, he or she was promised a discount (or a customer benefit) for calls to any member of this local network. On the other hand, no discount was offered for calls between the customer and the majority of irrelevant others in the network as a whole. MCI's Calling Circle was very attractive to individuals who needed to communicate frequently over long distances with their significant others. By launching this campaign, MCI was able to expand its share of the long-distance service market dominated by AT&T (Strouse 2001). The upshot was that this local bias could sustain customer benefits within the bound of acquaintance networks.

This paper confirms such local bias effects by developing a model of diverse network topology. In the past, it was difficult to study these effects because of

the lack of appropriate tools for analyzing complex social networks. Researchers had little choice but to ignore them. Recent advances in complexity theory, however, have provided us with a tool to examine the dynamics of complex social networks (e.g., Watts and Strogatz 1998). By developing network effect models with this tool, we show that incompatibilities persist under locally clustered networks, for example, a friends-and-family network. However, we also show that the winner-take-all markets are possible even when each consumer interacts with a small number of acquaintances. The different outcomes of market dynamics are explained by whether or not a network topology allows local bias to arise and persist in a social network.

This paper proceeds as follows. The second section reviews recent progress in complexity theory and introduces a tool for specifying diverse social networks. In the third section, we develop simulation models. The fourth section shows the results of our simulations. In the last section, key findings are highlighted, and their implications are discussed in light of the extant literature.

## 2. Networks of Interactions

This section briefly reviews the recent progress in complexity theory, which offers a tool for us to reinvestigate the winner-take-all hypothesis. As Strogatz (2001) noted, the current interest in networks could be considered part of a broader movement toward research on complex systems, where interactions among component parts make it difficult to understand the behaviors of whole systems. A network, in this view, is a blueprint for how those component parts interact. We present the related literature by dividing it into two categories: simple networks and complex networks. Then we briefly survey the burgeoning complexity research in the management area and discuss how our work is similar to and distinct from it.

### 2.1. Simple Networks

Until very recently, researchers could not work with the structure and dynamics of complex networks (Strogatz 2001). In the 1980s and 1990s, most mathematical models attempted to highlight the complexities arising from the dynamics of large interactive systems while sidestepping their structural complexities. In doing this, researchers favored simple networks coupled in geometrically regular ways. Such regular networks were especially popular in physics, where many phenomena exhibit spatial order by obeying the rule of local, nearest neighbor interactions.

This regular network topology has been applied to the study of social phenomena as well. For example,

Axelrod (1997) developed a model with a typical regular network assumption: Each individual interacts only with his or her nearest neighbors. His numerical model showed that differences in beliefs and attitudes could persist across groups. In studying local network effects, Cowan and Miller (1998) also used the simplest kind of regular network, or what economists call a “circular city” model—each agent interacts only with two immediate neighbors, one to the right and one to the left. This model shows that there exist multiple equilibria, only a small number of which represent technological standardization. The regular network topology is a reasonably good approximation of spatial phenomena where physical distance constrains social interactions. However, this structure has limitations for research that attempts to capture essential aspects of complex social networks (Strogatz 2001, Barabási et al. 1999). In particular, social distance, unlike physical distance, can violate the transitivity of distances (Barnett 1989, Watts 1999).

Another simple network topology that attracted much attention because of its beautiful mathematical properties is random networks. Unlike regular networks, random networks pay no attention to the role of physical distance. An individual in a random network can be connected to any other individual in the world. Graph theorists know that in the presence of such random connectivity, it takes only a few steps for everyone to reach everyone else, even in a large world with a great many individuals (Erdős and Rényi 1959, Bollobás 1985). This property was used to explain why the real world sometimes looks “small.” However, a plethora of studies have indicated that many real-world networks systematically deviate from the topology predicted by the random network theory (Ravasz and Barabási 2003).

## 2.2. Complex Networks

The past few years have witnessed an explosion of research on complex networks. This new trend departs significantly from the prior complexity research that has kept networks of interactions simple (Strogatz 2001). Watts and Strogatz (1998) ignited this explosion by offering a clue about how to tackle the complexity inherent in the structures of real networks. The key idea is that a complex network in the real world may lie between a regular network and a random network. The origin of this idea can be traced to Granovetter (1973, 1983), who envisioned social networks as amalgams of highly clustered subgroups and shortcuts (or what he called “social bridges”) connecting them. In particular, he saw the important role of shortcuts in job searches. He observed that successful job searches are often done through random contacts with individuals who are not close friends. Such

contacts, or shortcuts, can reduce the role of physical distance, which otherwise constrains social interactions within some physical proximity. Watts and Strogatz (1998) formalized this idea by developing an algorithm that can encompass the span of possible topologies between a regular network and a random network.

There are several advantages of using this complex network. First, physical distance is not a constraint on social interactions in this network. Using shortcuts, one can address social interactions that are unconstrained by physical distance. Second, the Watts-Strogatz network model allows researchers to examine the dynamics of a variety of complex networks by focusing on only a single parameter, which is associated with the availability of shortcuts. This quality is particularly appealing when researchers do not know where exactly the real world lies.<sup>2</sup> Third, the Watts-Strogatz network model captures the two essential features of many real-world networks: (1) high clustering and (2) low degrees of separation.

Of course, this network model cannot address all kinds of complexity found in reality. There are several limitations. First, Watts and Strogatz (1998) sidestepped the complexity of network evolution by assuming that networks are static. Second, all ties in the network are assumed to be equal. That is, the relative strength or weakness of a tie is ignored. Third, it has been shown that the connectivity distributions of the Watts-Strogatz network model with shortcuts can be approximated by Poisson distributions (Barabási et al. 1999). Empirical work provides some support for this property in acquaintance networks (Amaral et al. 2000). However, the Watts-Strogatz model is inappropriate to describe many real-world networks where hubs exist.<sup>3</sup>

## 2.3. Complexity Research in the Management Literature

Throughout the 1990s, the complexity movement gained popularity across a wide variety of disciplines, influencing research in management as well. Among various attempts, the complexity of the search for an optimal solution in coupled systems has attracted substantial attention (e.g., Levinthal 1997, Gavettie and Levinthal 2000, Rivkin 2000, Rivkin and Siggelkow 2003). Much of this work highlighted the effect of coupling topology on the difficulty of

<sup>2</sup> The authors thank one of the referees at *Management Science* for pointing out this advantage.

<sup>3</sup> Consider, for example, the browser “war” between Microsoft and Netscape. To win the market, Microsoft took advantage of the AOL network, which was a hub for many customers. Lee and Song (2003) developed a network effects model with hublike networks (Barabási et al. 1999) and found that stochastically dominating results are the winner-take-all outcomes.

searches, imitation, or strategic choices. Initially, the focus of network architecture was on the degrees of coupling, but now research is moving toward other elements of structural complexity.

In line with this stream of research, we are also interested in structural complexity. But we seek to shed light on how simple patterns can emerge from a market system where heterogeneous customers interact in a complex way. In particular, we examine the emergent dynamics from the perspective of structural complexity. Abrahamson and Rosenkopf's (1993, 1997) studies are closely akin to the spirit of our work. Their research showed that the structure of social networks affects whether innovations can diffuse throughout a whole system. Like Abrahamson and Rosenkopf (1997), we explicitly assume that the diffusion of new technologies is channeled through complex social networks. But, unlike them, we focus our analysis on the competition of incompatible technologies rather than the diffusion of a single technology. We argue that this type of competition does not always result in winner-take-all outcomes. The long-run outcomes depend on network topology. Using the Watts-Strogatz model as a representation of customers' diverse interaction networks, we reexamine the winner-take-all hypothesis.

### 3. The Model

We consider a model in which two incompatible products compete for customers. Like Arthur (1989), we focus mainly on the demand-side dynamics. Because a primary driving force behind product adoption is network effects or benefits, we start by modeling the competition among these products when network benefits come directly from the usage of each product. We assume that these *direct* benefits grow through interactions in an acquaintance network. Second, we extend this model by adding *indirect* network benefits, which derive from the availability of complements compatible with the focal product.

#### 3.1. Basic Model: Direct Network Effects

Let us first turn to the adoption dynamics of the basic model. Suppose that two incompatible, competing products A and B are introduced to the market simultaneously. The essence of adoption dynamics lies in an individual's sense of payoff from or utility gained in using each product. Formally, individual  $i$ 's payoff for adopting product  $j$  ( $j = A, B$ ) at time  $t$  is

$$u_{it}^j = r_i + aD_{i(t-1)}^j, \quad (1)$$

where  $r_i$  is customer  $i$ 's basic willingness to adopt a product,  $a$  measures the strength of network effects, and  $D_{i(t-1)}^j$  represents direct network effects.

Like many prior researchers (e.g., Katz and Shapiro 1985, Farrell and Saloner 1992), we assume  $r_i$  to be heterogeneous across customers. Like Katz and

Shapiro (1985), we assume that  $r_i < 0$  for the majority of customers. This assumption basically says that most customers are reluctant to adopt a new technology. The literature on the adoption of innovations indicates that this disposition typically follows a normal distribution (Rogers 1995). Thus, we assume  $r_i$  to follow a normal distribution with mean  $\mu$  and variance  $\sigma^2$ .

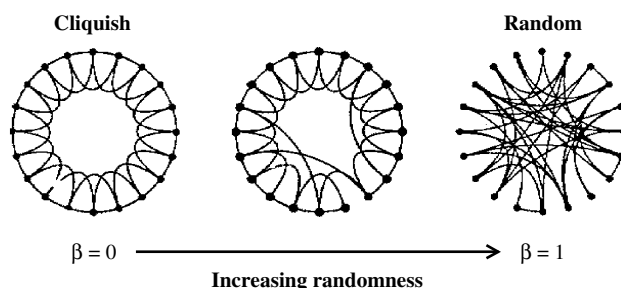
Now consider network effects or benefits. Much of the prior work (e.g., Katz and Shapiro 1985, Arthur 1989, Farrell and Saloner 1992) assumes that network benefits are proportional to the size of an installed base. Little distinction has been made between direct and indirect effects in modeling network effects. As discussed earlier, we believe that direct effects usually follow from interactions among customers. In addition, each customer's social interaction is restricted to a small number of acquaintances. For example, consider complex software. A customer may have a negative attitude toward it at first. As some of his or her friends or coworkers use it, they exchange advice or files with one another, increasing the value of the software in the customer's mind. Later, the focal customer may adopt it. The key difference between our work and previous work is that  $D_{i(t-1)}^j$  denotes a fraction of adopters of product  $j$  at time  $t - 1$  out of all of customer  $i$ 's acquaintances. Suppose the market consists of  $n$  customers. Then the proportion of adopters from a local view is

$$D_{i(t-1)}^j = \frac{1}{k_i} \sum_{h=1}^n \delta_{ih} \omega_{h(t-1)}^j, \quad (2)$$

where  $k_i$  is the total number of  $i$ 's acquaintances. The term  $\delta_{ih}$  has the value of 1 if  $i$  and  $h$  are connected and if  $i \neq h$ , and 0 otherwise;  $\omega_{h(t-1)}^j$  has the value of 1 if customer  $h$  adopted product  $j$  at time  $t - 1$ , and 0 otherwise.

**3.1.1. Social Networks.** To represent diverse social networks, we employ the Watts-Strogatz model (1998). This model can be built on a ring substrate with  $n$  nodes and  $k$  links per node, assuming that each of  $n$  customers maintains  $k$  relationships with others. An example is shown in Figure 1. Consider

Figure 1 Coupling Topology for Social Networks



Source: Watts (1999, p. 68).

a network on the left, where  $n = 20$  and  $k = 4$ . It is a regular network with a high degree of clustering. That is, the fraction of neighboring nodes that are also connected to one another is very high. To construct diverse kinds of conceivable social networks, one can rewire each link of this regular network by making random connections between nodes with probability  $\beta$ . When  $\beta = 0$ , the above structure will be preserved. When  $\beta$  is sufficiently small, the high degree of clustering will be preserved with a few random connections among subnetworks. But when  $\beta = 1$ , a network becomes random with poor clustering, as shown on the right. However, shortcuts are ubiquitous. So one way of interpreting  $\beta$  is as the number of shortcuts available in a social network. The larger the value of  $\beta$ , the more shortcuts there are in a network. In addition, as a result of random rewiring for  $\beta > 0$ , the number of neighboring nodes for each node varies.

**3.1.2. Adoption and Repurchase Processes.** Demand for a product is represented by new purchases and repurchases. New purchases of a product occur when customers adopt it for the first time. Repurchases are generated by experienced customers who have adopted the product in the past. Each customer buys one unit of either product A or B at every period.

A neophyte adopts either product A or B when Equation (1) is positive. We assume that there exist some early adopters who adopt products at  $t = 0$ , when network benefits are absent. Note that  $u_{i0}^A = u_{i0}^B = r_i$ . It is assumed that the early adopters adopt either A or B with a probability of 0.5. (This assumption will be relaxed later in a simulation experiment for analyzing the get-big-fast strategy.) Subsequently, the early adopters will influence their acquaintances. Over time, some customers among an early adopter's acquaintance network adopt product  $j$ . This adoption positively affects other neophytes' purchase decisions. When  $u_{it}^j > 0$  for all  $j$ , customer  $i$  chooses product  $j$ , of which  $u_{it}^j$  is larger.

Unlike much previous work, our model considers the possibility that an experienced customer can repurchase a product or switch to an alternative one at every  $t$  for  $t > 0$  when the alternative is of higher value to that customer. For instance, suppose that experienced customer  $i$  has already purchased product A at time  $t^*$ . The additional utility that he or she derives from switching to product B at time  $t$  for  $t > t^*$  is

$$\begin{aligned} u_{it}^B - u_{it}^A &= [r_i + aD_{i(t-1)}^B] - [r_i + aD_{i(t-1)}^A] \\ &= a[D_{i(t-1)}^B - D_{i(t-1)}^A]. \end{aligned} \quad (3)$$

If (3) is positive (that is,  $D_{i(t-1)}^B > D_{i(t-1)}^A$ ), experienced customer  $i$  switches to product B. Otherwise, customer  $i$  stays with product A.

### 3.2. Addition of Indirect Network Effects

In the previous model, each customer's decision is directly affected by the number of adopters among his or her acquaintances. Now we add indirect network effects. In some industries, the diffusion process of a competing product depends on the availability of a variety of complements. For example, when an individual buys a PC or a PDA, that decision is not only affected by acquaintances, but also by the availability of particular software products tailored to that individual's own needs.

Let  $I_{t-1}^j$  denote indirect network effects or benefits associated with complements for product  $j$  at time  $t - 1$ . Now, each customer's willingness to adopt is

$$u_{it}^j = r_i + aD_{i(t-1)}^j + mI_{t-1}^j, \quad (4)$$

where  $m$  is a customer's sensitivity to the availability of complements. If  $m = 0$ , there may be no complements. Then this model is the same as the basic model, Equation (1).

When  $m > 0$ , customer  $i$ 's decision is affected by the availability of complements for product  $j$ . When there are killer applications that are compatible with a given product,  $m$  could be large. Assuming that the presence of complements has a global effect on customer choice, we represent this effect as a function of the size of an installed base.<sup>4</sup> That is,  $I_{t-1}^j$  is a proportion of customers who adopted product  $j$  at time  $t - 1$ . Here, the implicit assumption is that the producers of complements invest in developing their products based on the size of product  $j$ 's installed base.

## 4. Results

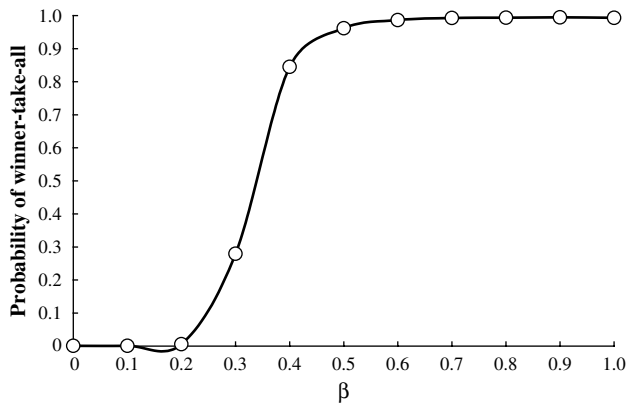
### 4.1. Results of the Basic Model

The simulation here seeks to show whether a winner-take-all process depends on the coupling topology of a social network. We assume that network products are attractive enough to let their demand take off. In particular we set  $\mu = -100$ ,  $\sigma = 50$ , and  $a = 500$ .<sup>5</sup> Recall that  $\mu$  and  $\sigma$  are the parameters for a normal distribution for each customer's basic willingness to adopt and that  $a$  measures the strength of network effects. We conducted a simulation experi-

<sup>4</sup> Although this is a typical assumption in the literature, it may not always represent reality. Sometimes complementary products may cause localized network effects. For example, DVD titles produced for the Korean market cannot be viewed on a DVD player bought in the United States. The authors thank Dan Levinthal for bringing this to their attention.

<sup>5</sup> Like other diffusion models (Abrahamson and Rosenkopf 1997, Rohlfs 2003), our model shows the possibility of underadoption. But we rule out this possibility by assuming that customers are willing to adopt the network products and that their network benefits are sufficient.

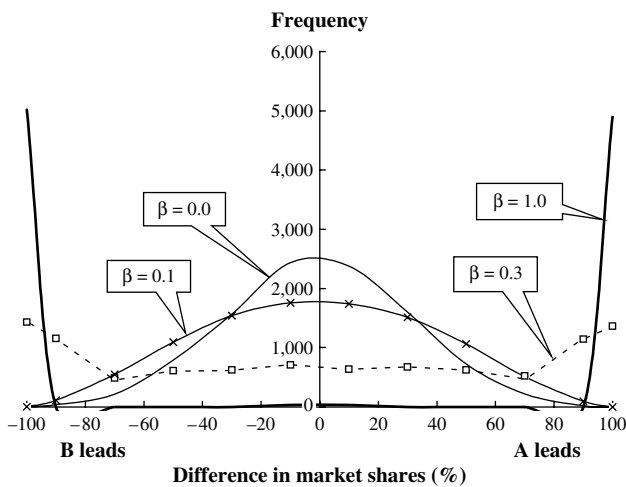
**Figure 2 Network Topology and Winner-Take-All**



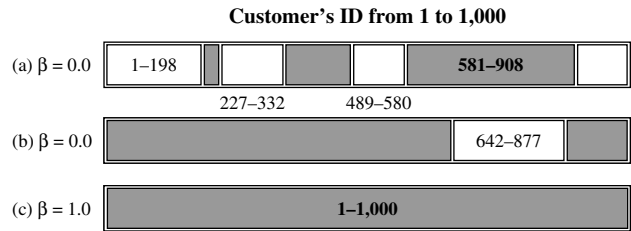
ment by varying the value of  $\beta$ , a tunable parameter for the Watts-Strogatz model with  $n = 1,000$  and  $k = 10$ . As indicated before, the number of shortcuts in a network is positively associated with the value of  $\beta$ . Figure 2 demonstrates that the winner-take-all possibility depends on  $\beta$ . The horizontal axis represents the value of  $\beta$ , and the vertical axis represents the probability of observing a winner-take-all outcome. This probability was estimated based on 10,000 trials. When  $\beta < 0.2$ , the probability of observing a winner-take-all outcome is zero. That is, the system lies in the market-sharing regime, where the two technologies always coexist at the steady state. On the other hand, when  $\beta > 0.5$ , the winner-take-all probability is almost 1, or one technology (either A or B) almost always corners the market. When  $0.2 \leq \beta \leq 0.5$ , our result shows an abrupt transition from the market-sharing regime to the winner-take-all regime.

Figure 3 shows frequency distributions for diverse long-run outcomes with variation in  $\beta$ . The horizontal axis represents a difference between technology A's market share and technology B's market share, and the vertical axis represents its frequency over 10,000

**Figure 3 Market Sharing vs. Market Cornering**



**Figure 4 Shared Markets and Winner-Take-All Markets: Examples of Single Realizations at the Steady State**



Note. ■ represents an adopter of product A, and □ represents an adopter of product B.

simulation runs. When the value of  $\beta$  is high, the frequency distribution shows a bimodal structure. For example, when  $\beta = 1$ , two modes are located either at  $-100\%$  or  $100\%$ . This means that either technology A or technology B corners the market. Figure 4(c) illustrates an example of this sort of winner-take-all market; this is a single realization of a typical run. All the customers (from ID 1 to 1,000) adopted technology A in this particular trial. But we cannot predict which technology will corner the market. A chance event, or a small historical event, determines the destiny of adoption dynamics. This is similar to the result of Arthur's (1989, 1994) study.

However, our result indicates that if the customer network is highly cliquish, with few shortcuts, network effects do not lead to winner-take-all outcomes but to market-sharing outcomes. When  $\beta = 0$ , the frequency distribution looks like a bell-shaped curve centered at 0. This means that the majority of trials show a tendency toward a shared market, and incompatibilities persist. Figures 4(a) and 4(b) illustrate examples of a shared market. It is rather striking that technology B is sustained in Figure 4(b) despite its small installed base (customer ID 642 to 877).

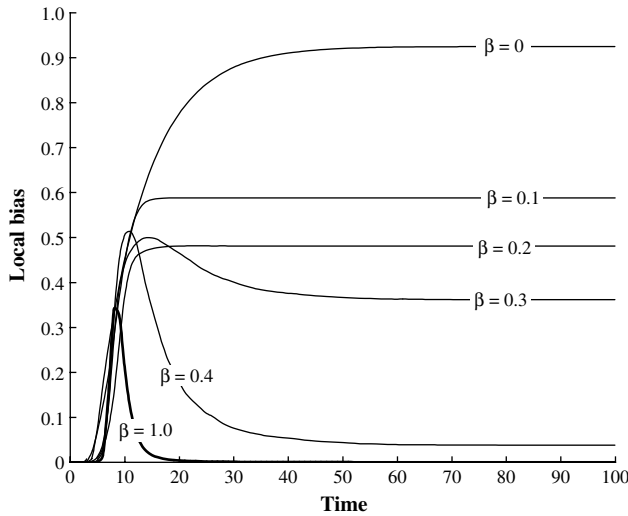
Why do winner-take-all outcomes sometimes arise, and why do market-sharing outcomes arise at other times? To answer this question, we examine local bias in diverse networks. Recall that the key assumption of the basic model is that a customer's purchase decision is directly affected by his or her acquaintances. Due to the small size of this acquaintance network, a customer's information can sometimes be biased. We measure local bias as follows:

$$\text{Local bias} = \frac{\sum_{i=1}^n |(s_i^A - s_i^B) - (s^A - s^B)|}{n}, \quad (5)$$

where  $s_i^A$  and  $s_i^B$  are the shares of technologies A and B in customer  $i$ 's acquaintance network, respectively, and  $s^A$  and  $s^B$  are the market shares of technologies A and B in the entire market, respectively.

Figure 5 shows variation in the level of local bias by network structure. The horizontal axis represents simulation time, and the vertical axis represents the level of local bias. The simulation results show that the lev-

Figure 5 Local Bias over Time

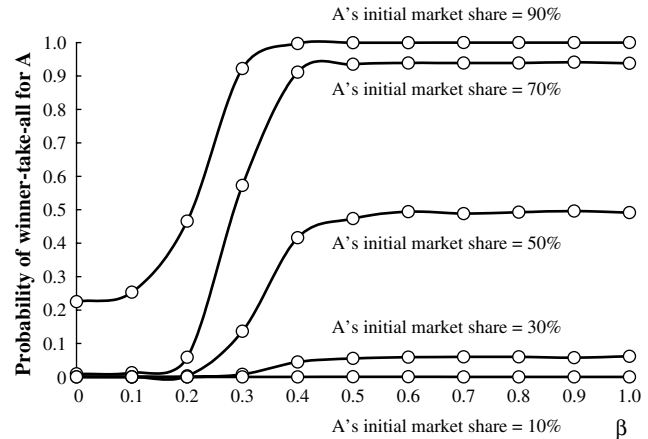


els of local bias for all cases reach the steady state over time. The level of bias at the steady state depends on the connection topology of a customer network: The smaller the value of  $\beta$ , the higher the level of bias. When  $\beta = 1$ , local bias quickly disappears. This happens despite the fact that a customer's choice is still affected by a small number of acquaintances. Thus, the steady-state behavior of a random network resembles that of a global effects (installed base) model, which has no bias. On the other hand, the level of local bias is highest when  $\beta = 0$ . Here the customer network tends to be clustered around densely connected neighboring nodes. Such cliquishness seems to let each customer retain local bias, making a locally based decision. As a result, a small incompatible niche (like the one shown in Figure 4(b)) can be sustained.

4.2. Simulation Experiment for the Get-Big-Fast Strategy

In the basic model, we assumed that all the competitors started with the symmetric condition: Early adopters adopted either A or B with a probability of 0.5. What would happen if competitors started from systematically different installed bases? This question is associated with the effectiveness of the get-big-fast strategy discussed in the introduction. To answer this question, we conducted another simulation experiment. A key experimental variable is market share for the early adopters. The literature indicates that firms tend to compete hard for early adoptions, usually through pricing aggressively or giving away goods. Although our model does not specify price explicitly, penetration pricing or free goods can affect each individual's basic willingness to adopt. Thus, one can interpret an early market share as a firm's costly initial investment for winning the market in the future. A larger market share means that the firm has invested a lot.

Figure 6 Effect of Differential Starting Positions



The question arises as to whether this costly investment will pay off in the long run. There are many complex ways to address this question. One simple, meaningful approach is to assess the probabilities of achieving winner-take-all outcomes for various levels of initial market shares. Obtaining the monopoly position is meaningful because it enables a firm to recoup the cost of an early investment by raising the price of its product. This is known as the "bargain-then-rip-off" strategy (Farrell and Klempner 2001).

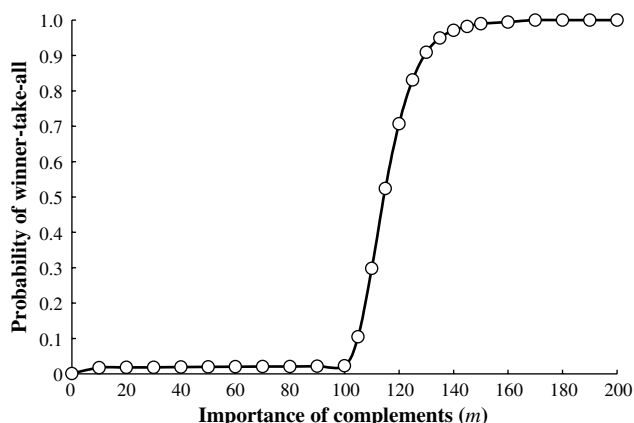
Figure 6 shows that it is hard to win the market completely when  $\beta = 0$  or when  $\beta$  is sufficiently small. When firm A achieves a 70% market share early on (firm B achieves a 30% market share), the probability of A's winning the whole market is almost zero. Even when it aggressively achieves a 90% market share at the beginning (firm B achieves a 10% market share), the winner-take-all probability is only about 0.2. This result suggests that the get-big-fast strategy is less likely to be successful when  $\beta = 0$ . In particular, if all the competitors set prices below their costs to attract adopters, they may suffer from losses without clear benefits.<sup>6</sup> On the other hand, when  $\beta > 0.4$ , the get-big-fast strategy is more likely to work. As A's early market share surpasses B's, the probability of A's winning the whole market gets closer to 1. In this situation, the early, costly investment of building an installed base is more likely to pay off.

4.3. Simulation Experiment for the Effect of Complements

What would happen if the availability of complements also influences competition? Could it dilute the

<sup>6</sup> For the brevity of our presentation, we do not elaborate on this, but our model does show this possibility. We modeled the "bargain-then-rip-off" strategy by specifying price and cost explicitly. We found that all the competitors continuously suffered from losses when  $\beta = 0$  or  $\beta$  is sufficiently small.

Figure 7 Effects of Complements ( $\beta = 0.0$ )



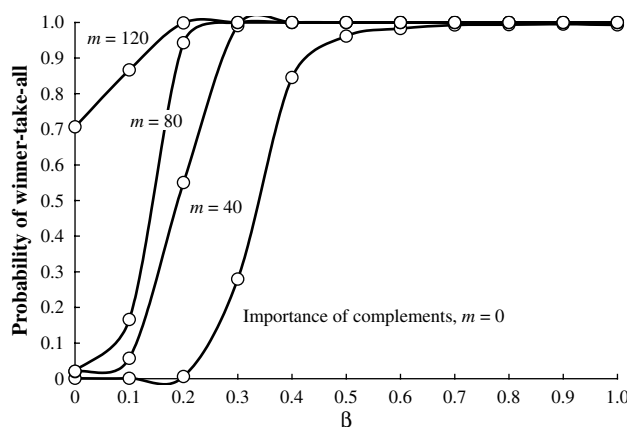
effect of local bias in a highly clustered network? First, we restrict our analysis to a highly clustered network, namely one in which  $\beta = 0$ , because a network with substantial random connectivity ( $\beta > 0.4$ ) shows little local bias. The result of the simulation is shown in Figure 7. The horizontal axis represents the importance of complements (i.e., variation in  $m$ ) holding *direct network effects* constant. The vertical axis represents the probability of observing a winner-take-all outcome based on 10,000 trials. When there is no effect of complements, or when  $m = 0$ , the winner-take-all possibility is obviously zero. The result does not change much until  $m$  increases to 100. Beyond this point, the winner-take-all probability abruptly increases with any small increase in  $m$ . When  $m \geq 140$ , the winner-take-all probability approaches one. This indicates that the importance of complements relative to direct network effects could dilute the effect of local bias in a highly clustered network, making the market tip toward a single dominant technology.

Figure 8 shows how an increase in the importance of complements ( $m$ ) shifts the original curve ( $m = 0$ ) shown in Figure 2.<sup>7</sup> The increase in  $m$  shifts the original curve upward to the left. The curves on the left ( $m > 0$ ) indicate that a transition to the winner-take-all regime is possible with a lower value of  $\beta$ . That is, the winner-take-all tendency is more likely with fewer shortcuts, when the availability of diverse complements damps down the effect of local bias.

The findings here recast light on the evolution of the VCR industry. The original intended use of the VCR was to record broadcast programs or to make and view home movies (Cusumano et al. 1992, Rohlfs 2003). Customers initially did not show much interest in prerecorded tapes. But customers might have exchanged their own recorded broadcast programs or

<sup>7</sup> The authors thank Dan Levinthal for bringing this idea to their attention.

Figure 8 Effects of Complements



home movies with their significant others. Thus,  $m$  would have been small or 0 in this early period. Our result suggests that Sony's Beta would not have been driven out if  $m$  had remained small. But there was a big change from 1982 to 1986. Sales and rentals of prerecorded cassettes grew dramatically, making customers sensitive to the availability of prerecorded tapes—that is, the value of  $m$  increased. Cusumano et al. (1992, p. 88) noted: “[T]he dominance of VHS in tape-rental channels hastened the demise of Beta and made certain it would not survive even as a second format.” Our simulation result here is not inconsistent with the story of VHS versus Beta.

#### 4.4. Sensitivity Analysis

We did a sensitivity analysis for selected parameters. First, we varied the value of  $k$  to see if our results were sensitive to the number of acquaintances per individual. We found that our results were not sensitive to a change in  $k$  as far as  $k \ll n - 1$ . Note that when  $k = n - 1$ , the network becomes a fully connected network or global network. A few results of the sensitivity analysis are selected and presented in the appendix. Second, we conducted a sensitivity analysis by varying  $n$ , the total number of customers in the market. Our results are insensitive to a change in  $n$ . In addition, we checked the robustness of our replacement condition—each customer was assumed to make a repeat purchase at every period. One can relax this replacement assumption such that each customer can replace the existing product with a new one at every 5th period, every 10th period, or every 100th period. The increase in length of the replacement cycle implies that a product is a durable good. Our sensitivity analysis indicates that durable goods assumptions increase the time to reach a steady state but do not affect the essence of the dynamics. The advantage of the every-period-replacement assumption in our simulations, then, lies in the substantial reduction of the computational burden for running simulations.



## 5. Conclusion

We have developed simulation models to examine under what conditions the winner-take-all hypothesis is valid. We found that the winner-take-all outcome depends on the structural characteristics of a customer network. In a highly clustered network, neighboring individuals tend to know one another quite well, but no or few shortcuts bridge the gap between remotely located subnetworks. Our study showed that local bias tends to be preserved in this type of network. The preservation of this bias limits the tendency for a lead product to drive out its rivals. It may explain why marketers can often observe the clustering phenomenon, as Rosen (2000, p. 63) illustrates:

In marketing End-Note to the academic market, our company often came across university departments that were defined as “All Macintosh” or “All PC.” Software usage followed the same pattern: You could find a cluster of WordPerfect users in one building at a university and a cluster of Microsoft Word users in another building.

On the other hand, our study showed that this kind of local bias is unlikely to be preserved in the network that has a sufficiently large number of shortcuts. The literature on diffusion indicates that frequent travelers act as shortcuts in a social network, leaving its subnetworks open to outside forces (Rogers 1995). This openness attenuates local bias over time. In such a situation, there is no mechanism to curb the outgrowth of a lead technology, and adoption dynamics are driven to the winner-take-all outcome.

In addition, we investigated whether the above result would change with the availability of diverse complements, which is assumed to have global effects on consumer choice. We found that the effects of complements, when they are large relative to direct network effects, can damp down the effects of local bias. Then a lead technology can drive out the alternative even in a highly clustered network.

Emphasizing the installed base while deemphasizing network topology, prior work has shown that the market has a tendency to tip toward a single dominant technology (e.g., Arthur 1989). Recently Farrell and Klemperer (2001) extensively reviewed research on network effects. This thorough review contains no single discussion of the role of network topology. Given the complexity of studying social networks, the paucity of research on the issue may have been understandable. However, rapid advances in complexity theory now offer many tools to cope with this complexity. Strogatz (2001, p. 268) noted: “Researchers are only now beginning to unravel the structure and dynamics of complex networks.” We believe considerations of structural complexity can enrich our understanding about how networks shape competition and

firm strategy in the “network economy.” Our work took only a first step in this direction. We believe many promising opportunities lie ahead.

The winner-take-all hypothesis has been popular for practitioners as well. Often, such popularity leads laymen to generalize its implications without careful consideration. Unsurprisingly, many consultants and practitioners were quick to draw strategic implications from the literature. Popular examples are the ideas that a product must “get big fast” or that a firm must “build the installed base first before making any profit.” Indeed, many dot-com companies quickly acted on these ideas in the late 1990s. Not many of them, however, were able to sustain their efforts in this direction for long. It turns out that the implications of the winner-take-all hypothesis have been, at best, confusing to practitioners.

In an attempt to help these managers and entrepreneurs, our study sorted out some conditions under which the winner-take-all outcome will or will not occur. Our study showed that local bias can persist if customers interact only with well-known others and if this interaction is a main source of customer benefits. In this case, the winner-take-all hypothesis may not be valid. Smaller rivals can fortify their customer networks against large firms’ attacks. This bias may provide some clue as to why Apple still survives as a niche player despite prevalent doomsday predictions in the late 1990s about its failure. Furthermore, smaller rivals can encourage these customers to act as sales representatives and to foster local bias, as was illustrated in the MCI case. When local bias persists, our study suggests that the get-big-fast strategy could result in a waste of scarce resources with no clear gain.

On the other hand, our study also suggests that the managerial implications associated with the winner-take-all hypothesis remain valid when local bias cannot persist for long. Our study found two conditions under which this may be valid. First, the presence of substantial shortcuts in a network tends to reduce local bias. Second, local bias in many cases cannot be preserved when the value of a product comes mainly from the availability of diverse complements rather than from interactions among customers. In this case, producers of complements rely on the size of the focal product’s installed base to market their own products. Here the get-big-fast strategy may be an inevitable choice.

Our finding seems to cast a new light on the classic story of competition between VHS and Beta (Cusumano et al. 1992). Had customers’ main use for VCRs remained recording broadcast programs or making and viewing home movies, Beta could have survived as a second format. The problem with

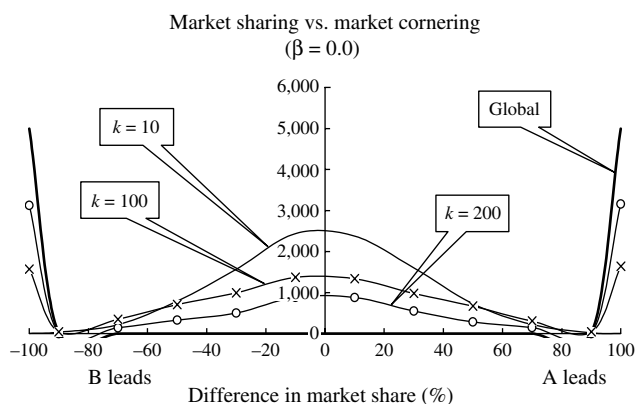
Sony's Beta technology was that it could not maintain the local bias as the market for prerecorded tapes emerged and as more and more movie tapes—the main source of customer benefits—became available for VHS.

To highlight how network topology affects adoption dynamics, our study sidestepped many complexities in reality by imposing simplifying assumptions. First, we considered the competition of two incompatible technologies only when they are introduced simultaneously. An interesting and important extension of our model would be to consider sequential entry, where one technology is introduced first and a new incompatible technology arrives later. We believe such a sequential entry model would provide valuable theoretical and practical implications. Second, we could not extend the analysis beyond two competing models. Consequently, we do not know whether the main findings of this study remain intact in a general case of many competing, incompatible products. Third, we used the Watts-Strogatz model as a representation of diverse social networks. The key assumptions of this model are: All relationships among customers are symmetric and of equal significance; they are assumed to be fixed over time; and no hubs exist. Obviously, these are idealizations of reality. Future research may reexamine the issues considered here by relaxing some of these simplifying assumptions.

### Acknowledgments

The authors are grateful to the editor, Dan Levinthal, two anonymous referees at *Management Science*, as well as Duncan J. Watts, Kyungmook Lee, Sankyo Rho, and Sangwook Park. The authors also thank seminar participants at Columbia University, Seoul National University, and the University of Pennsylvania.

### Appendix. Sensitivity Analysis for $k$



Note. "Global" represents a fully connected network or  $k = n - 1$ , where  $n$  is the total number of individuals in the network and  $k$  is the number of acquaintances per individual.

### References

- Abrahamson, E., L. Rosenkopf. 1993. Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion. *Acad. Management Rev.* **18**(3) 487–517.
- Abrahamson, E., L. Rosenkopf. 1997. Social network effects on the extent of innovation diffusion: A computer simulation. *Organ. Sci.* **8**(3) 289–309.
- Amaral, L. A. N., A. Scala, M. Barthelemy, H. E. Stanley. 2000. Classes of small world networks. *Proc. Natl. Acad. Sci. USA* **97**(21) 11149–11152.
- Arthur, W. B. 1987. Competing technologies: An overview. G. Dosi, ed. *Technology Change and Economic Theory*. Columbia University Press, New York, 590–607.
- Arthur, W. B. 1989. Competing technologies, increasing returns, and lock-in by historical events. *Econom. J.* **99**(394) 116–131.
- Arthur, W. B. 1994. *Increasing Returns and Path Dependence in the Economy*. University of Michigan Press, Ann Arbor, MI.
- Arthur, W. B. 1996. Increasing returns and the new world of business. *Harvard Bus. Rev.* **74**(4) 101–109.
- Axelrod, R. 1997. The dissemination of culture: A model with local convergence and global polarization. *J. Conflict Resolution* **41**(2) 203–226.
- Barabási, A.-L., R. Albert, J. Hawoong. 1999. Mean-field theory for scale-free random networks. *Physica A* **272** 173–187.
- Barnett, G.A. 1989. Approaches to non-Euclidean network analysis. M. Kochen, ed. *The Small World*. Ablex, Norwood, NJ, 349–372.
- Bollobás, B. 1985. *Random Graphs*. Academic Press, London, UK.
- Cowan, R., J. H. Miller. 1998. Technological standards with local externalities and decentralized behavior. *J. Evolutionary Econom.* **8** 285–296.
- Cusumano, M. A., Y. Mylonadis, R. S. Rosenbloom. 1992. Strategic maneuvering and mass-market dynamics: The triumph of VHS over Beta. *Bus. Hist. Rev.* **66**(1) 51–94.
- Erdős, P., A. Rényi. 1959. On random graph I. *Publ. Math. Debrecen* **6** 290–297.
- Farrell, J., P. Klemperer. 2001. Coordination and lock-in: Competition with switching costs and network effects. Working paper, University of California, Berkeley, CA.
- Farrell, J., G. Saloner. 1986. Installed base and compatibility: Innovation, product preannouncement, and predation. *Amer. Econom. Rev.* **76**(5) 940–944.
- Farrell, J., G. Saloner. 1992. Converters, compatibility, and the control of interfaces. *J. Indust. Econom.* **40**(1) 9–35.
- Gavetti, G., D. Levinthal. 2000. Looking forward and looking backward: Cognitive and experiential search. *Admin. Sci. Quart.* **45**(1) 113–137.
- Granovetter, M. S. 1973. The strength of weak ties. *Amer. J. Sociol.* **78**(6) 1360–1380.
- Granovetter, M. S. 1983. The strength of weak ties: A network theory revisited. *Sociol. Theory* **1** 203–233.
- Katz, M. L., C. Shapiro. 1985. Network externalities, competition, and compatibility. *Amer. Econom. Rev.* **75**(3) 424–440.
- Katz, M. L., C. Shapiro. 1986. Technology adoption in the presence of network externalities. *J. Political Econom.* **94**(4) 822–841.
- Katz, M. L., C. Shapiro. 1992. Product introduction with network externalities. *J. Indust. Econom.* **40**(1) 55–83.
- Kelly, K. 1998. *New Rules for the New Economy: Ten Radical Strategies for a Connected World*. Penguin Books, New York.
- Kristiansen, E. G. 1998. R&D in the presence of network externalities: Timing and compatibility. *RAND J. Econom.* **29**(3) 531–547.
- Langlois, R. N., P. L. Robertson. 1992. Network and innovation in a modular system: Lessons from the microcomputer and stereo component industries. *Res. Policy* **21** 297–313.

- Lee, J., J. Song. 2003. Incompatible entry in small-world networks. *The Wharton Technology Mini-Conference, April 25*, The Wharton School, University of Pennsylvania, Philadelphia, PA.
- Levinthal, D. 1997. Adaptation on rugged landscapes. *Management Sci.* **43**(7) 934–950.
- Liebowitz, S. J. 2002. *Re-Thinking the Network Economy: The True Forces that Drive the Digital Marketplace*. Amacom, New York.
- Ravasz, E., A.-L. Barabási. 2003. Hierarchical organization in complex networks. *Physical Rev. E* **67** 026112.
- Rivkin, J. W. 2000. Imitation of complex strategies. *Management Sci.* **46**(6) 824–844.
- Rivkin, J. W., N. Siggelkow. 2003. Balancing search and stability: Interdependencies among elements of organizational design. *Management Sci.* **49**(3) 290–311.
- Rogers, E. M. 1995. *Diffusion of Innovations*. Free Press, New York.
- Rohlf, J. H. 2003. *Bandwagon Effects in High-Technology Industries*. MIT Press, Cambridge, MA.
- Rosen, E. 2000. *The Anatomy of Buzz: How to Create Word of Mouth Marketing*. Doubleday, New York.
- Shapiro, C., H. R. Varian. 1999. *Information Rules: A Strategic Guide to the Network Economy*. Harvard Business School Press, Cambridge, MA.
- Strogatz, S. H. 2001. Exploring complex networks. *Nature* **401**(8) 268–276.
- Strogatz, S. H. 2003. *Sync: The Emerging Science of Spontaneous Order*. Hyperion Press, New York.
- Strouse, K. G. 2001. *Marketing Telecommunications Services: New Approaches for a Changing Environment*. Artech House, Boston, MA.
- Watts, D. J. 1999. *Small Worlds: The Dynamics of Networks between Order and Randomness*. Princeton University Press, Princeton, NJ.
- Watts, D. J., S. H. Strogatz. 1998. Collective dynamics of “small-world” networks. *Nature* **393**(4) 440–442.