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NETWORK STRUCTURE EFFECTS ON INCUMBENCY ADVANTAGE

JEHO LEE,[1,*] JAEYONG SONG,[1] and JAE-SUK YANG[2]
[1] *Department of Strategy and International Management, Graduate School of Business, Seoul National University, Seoul, Korea*
[2] *The Sanford C. Bernstein & Co. Center for Leadership and Ethics, Columbia Business School, Columbia University, New York, New York, U.S.A.*

Research summary: *The literature on network effects has implicitly assumed that an increase in the size of the installed base magnifies network effects, which is a source of incumbency advantage. We argue that the overemphasis on this relationship has resulted in controversy and confusion in the literature, where the role of social networks remains largely unaddressed. By developing computational models of network effects with various network structures, we show that social distance in a customer network plays a moderating role that strengthens or weakens the relationship between the installed base and network effects, which in turn, affects the durability of incumbency advantage. When the average social distance between members in a customer network is large, the incumbency advantage will not be amplified, and an entrant with an incompatible product or service may find ways into the market. On the other hand, when the average social distance is small, early entry with a growing installed base will magnify incumbency advantage.*

Managerial summary: *In evaluating the strength of incumbency advantage or determining the price of an early mover, the size of the installed base has been widely used. We find that it is not a sufficient statistic, and confusion and error appear to result from assuming that it is. Our study suggests that degrees of separation, a measure of social distance in a network, can provide managers with an additional yardstick to sharpen their evaluation. When customer networks are characterized by fewer degrees of separation, the conventional use of the installed base as a metric may be reasonable. On the other hand, when customer networks are characterized by larger degrees of separation, the conventional use may potentially mislead managers in their decision-making. Thinking about the roots of user benefits (e.g., access to a few significant others vs. hubs) may be a reasonable starting point for assessing degrees of separation in a customer network.*

INTRODUCTION

Over the last three decades, numerous studies have examined the relationships among the installed base, network effects, and the durability of competitive advantage (e.g., Arthur, 1989; Farrell and Saloner, 1985; Katz and Shapiro, 1985; Lee, Lee, and Lee, 2003; Lee, Lee, and Lee, 2006; Schilling, 2002; Zhu and Iansiti, 2012). Network effects are defined as user benefits arising from compatibility among different users, enabling them to interact or trade with other users or use the same complementary products (Farrell and Klemperer, 2007). The received view is that the benefits of adopting a network product or service grow as its installed base, or the total number of adopters, increases. In his seminal theoretical work, Arthur (1989) derived a prediction popularly known as the "winner-take-all" outcome. When two or more incompatible products compete for customers, the product with the larger installed base magnifies customer benefits. According to Arthur, the leading product with more benefits will attract more customers, whereas lagging

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*Correspondence to: Jeho Lee, 599 Gwanangno, Gwanak-gu, Seoul, 151–916, Korea. E-mail: jeho0405@gmail.com

products with fewer benefits may lose their market shares. Over time, this self-reinforcing process, or positive feedback process, will amplify the advantage for the leading firm with the larger market share, thereby increasing incumbency advantage.

However, critics have argued that the benefits and durability of strong network effects have been overemphasized (e.g., Liebowitz, 2002; Liebowitz and Margolis, 1990; Schmalensee, 2000). The self-reinforcing relationship between an installed base and customer benefits is an important assumption that leads to the winner-take-all outcome in Arthur's (1989) theoretical work. However, this assumption has been controversial, leading to confusion among managers and policymakers. For example, on the eve of the new millennium, the instant messaging (IM) market was dominated by America Online (AOL). Although AOL's large installed base was at the heart of the antitrust policy debate, the advantage based on its installed base was not amplified over time. In recent years, Facebook has built up a huge installed base in many countries. However, the size of Facebook's installed base has neither driven out other social networking services nor blocked new entrants to the market. Our observation of these anomalies motivated the present study.

Like research on network effects, the broad strategy literature has been largely inconclusive regarding whether or not incumbency or first-mover effects confer durable competitive advantage (e.g., Ethiraj and Zhu, 2008; Lieberman and Montgomery, 1988; Mitchell, 1991). The implications of these mixed results in the literature are often conflicting and confusing to both laymen and practitioners. Due to the complexity of the phenomena, development of a broadly applicable theory appears to be very difficult. As Camerer (1991) suggested, it may be fruitful, at least for the moment, to focus on developing theories of middle range by identifying the boundary conditions under which incumbency advantage may or may not be durable. Indeed, Mitchell (1991) took an early step in this direction.

The objective of our work is to identify such boundary conditions by focusing on the structure of social networks, which has been largely unaddressed in the discussion of incumbency advantage. Social networks come in different shapes and have various network properties (Carter and Levy, 2012). Network structure is especially relevant to social networking services, such as Facebook and Twitter, where user benefits mainly come from user–user interactions. Recently, these social media gained popularity and made their way into mainstream society, and companies began to use them to listen and respond to their customers, who can tell their friends their happy or unhappy feelings about a company's service or product with just a few clicks (Kerpen, 2011). Word-of-mouth marketing has long been considered as a very effective way to influence customers' choices, but little has been known about how to trigger a word-of-mouth process. Recently, some social media began to provide companies with systematic tools to influence channels through which words can spread.

The main focus of our theoretical work in this study is degrees of separation, a measure of distance in social networks. We view this factor as a moderator that sometimes strengthens (via a self-reinforcing process) and at other times weakens (in the absence of a self-reinforcing process) the relationship between the installed base and network effects. In particular, we demonstrate numerically that the degrees of separation in a customer network determine the boundary conditions for durable incumbency advantage. When customer networks are characterized by fewer degrees of separation, a large installed base confers incumbency advantage in the presence of the self-reinforcing process described above. In these cases, early entry is crucial for firm survival.

On the other hand, when a customer network is characterized by larger degrees of separation, the self-reinforcing relationship between the installed base and network effects is no longer guaranteed. Consider, for example, the benefits (network effects) to typical users of IM or Facebook. These benefits do not come from all individuals in the installed base, but mostly from direct exchanges with a small number of significant others. Furthermore, strangers are not allowed to contact most users. This built-in mechanism limits both the scope of the network's connectivity and incumbency advantage. In this situation, we show that incumbency advantage is limited, and that latecomers have a better chance of survival.

This paper is organized as follows. First, we review recent advances in complexity theory, which have offered tools for tackling the complexity of social networks. Applying a new perspective based on this research, we develop our propositions. Second, we build models of incumbency advantage based on network effects, using some of these tools. Finally, we discuss the implications of our findings in light of the extant literature.

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THEORY AND PROPOSITIONS

One argument that has gained popularity in research on network effects is that an entrant with a new incompatible technology may not gain a foothold in markets where an incumbent has built up a large installed base (Arthur, 1994). David's (1985) historical work on QWERTY, the standard keyboard in use today, has been used as historical evidence for this argument. QWERTY has persisted since its introduction in 1873 despite the fact that an allegedly more efficient design became available later on. Despite the popularity of this argument, it has triggered bitter debate in the literature. Liebowitz and Margolis (1990) noted that the history of technology competition has very few examples of lock-in to an inferior technology. For example, recent empirical work on the home video game industry by Shankar and Bayus (2003) does not support Arthur's argument. Invoking the notion of creative destruction (Schumpeter, 1950), some critics have argued that innovative entrants can wipe out incumbency advantage based on network effects (e.g., Farrell and Klemperer, 2007; Liebowitz, 2002; Schmalensee, 2000).

A stream of theoretical research has tried to shed light on this debate by building sequential entry models. In a setup typical of these models, an early mover builds up its market share alone at stage one. Then an entrant introduces a new incompatible product or service, thereby competing for a customer base. Prior work has shown that the survival of the entrant depends on the incumbent's market share (i.e., its installed base), the date of introduction of the new product or service, costs, strategic pricing, consumer heterogeneity, and the quality of the network products or services (e.g., Farrell and Klemperer, 2007; Farrell and Saloner, 1985; Katz and Shapiro, 1992; Lee *et al.*, 2003; Zhu and Iansiti, 2012).

In determining the value of a network, prior research has predominantly regarded the installed base as the most important factor. At the heart of durable incumbency advantage lies the winner-take-all process, which requires a special assumption that the relationship between an installed base and the benefits of adoption (network effects) is self-reinforcing. In this regard, Arthur (1989: 124) noted: "It is … not sufficient that a technology gains advantage with adoption: the advantage must (at some market share) be self-reinforcing."

Ironically, nowhere can one find a "network" in typical network effect models. For example, it is hard to find any network in Arthur's (1989) mathematical model. This raises the question as to why the phenomenon was ever called "network effects" when discussion of the network itself seems to be missing. We argue that Arthur's self-reinforcing or positive feedback process arises in certain types of networks, but is not guaranteed to occur in other types of networks. In the following sections, we identify the boundary conditions for incumbency advantage by explicitly taking network structure into account.

Key network properties

The paucity of research on networks in general stems from their bewildering complexity, which often defies analytical tractability (Strogatz, 2001). Until recently, researchers have had difficulty even describing or representing social networks mathematically. The past 15 years, however, have seen an explosion of research on the structure and dynamics of networks, offering systematic ways to cope with the complexity inherent in social networks (e.g., Barabási, 2002; Buchanan, 2002). We briefly review this new stream of research with a focus on three key related network properties: (1) degrees of separation, (2) distribution sequence, and (3) clustering. In particular, we use these properties to unpack the puzzling relationship between the installed base and network effects.

Degrees of separation

Degrees of separation represent social distance between members of a network. Consider a complete network, an extreme type of network with the smallest average distance between nodes. Here, every individual is directly connected to every other individual. A family network is an example of this type. When any two family members are selected at random, each is always one step away from the other. In technical terms, a network of this sort has a characteristic path length of one, or one degree of separation.

The complete network has been the implicit basis for customer networks in the literature on network effects. This approach is consistent with the typical assumption of full information in economic models—every economic agent knows what every other agent has been doing (e.g., has complete

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knowledge of who adopted what). An attractive quality of this approach is that specific details about the network are unnecessary. This explains the absence of details about the network in Arthur's (1989) mathematical model on network effects. Furthermore, the simple structure of the complete network enables rigorous mathematical analysis.

However, the complete network assumption is unrealistic for representing customer connectivity in the market. When the number of individuals in a network increases by N, the number of possible connections increases by $N(N-1)/2$. When N is sufficiently large, it becomes unrealistic for every customer to interact with every other customer in the market, and the degrees of separation tend to grow in the absence of mechanisms to reduce them. Therefore, a more reasonable assumption in a large network is that each customer usually maintains contact with a small number of other customers. Consider the case of the Buddy List for instant messaging (IM) in the 1990s. AOL estimated that its clients built up lists of about 20–50 people (*The Ottawa Citizen*, 1999). Obviously, no user can build up a network that includes all the other users in the market. Such a long list would not feasibly fit onto the computer screen, nor would it be useful, since the benefits of IM use come from exchanges with significant others.

Recent studies in complexity theory have offered some meaningful ways to characterize large-scale networks in the form of "large-world" and "small-world" networks. A network is a large-world network, or a network of local interaction, when the number of degrees of separation grows linearly with the size of the network (Watts and Strogatz, 1998). An extreme theoretical possibility is the connected caveman network in Figure 1, in which distinct local subnetworks are nearly isolated from one another (Fang, Lee, and Schilling, 2010; Watts, 1999). Consider, for example, users of corporate IM in a company that restricts connections to outside individuals for security purposes. This restriction localizes interactions among individuals mainly within the boundaries of the company, isolating this corporate IM subnetwork from other IM subnetworks. Individuals in the corporate IM subnetwork tend to converse with many of the same nearby work acquaintances. Granovetter (1973) argued that information traversing through such a network is likely to be limited to a few clicks, which tend to share redundant ties. They tend to increase the number of steps needed for an individual to reach out to another individual in an entire network composed of multiple IM subnetworks (the characterization here does not rule out the possibility of disconnection between subnetworks). In this example, the network depicts a fairly large number of degrees of separation between individuals; it is thus a large-world network.

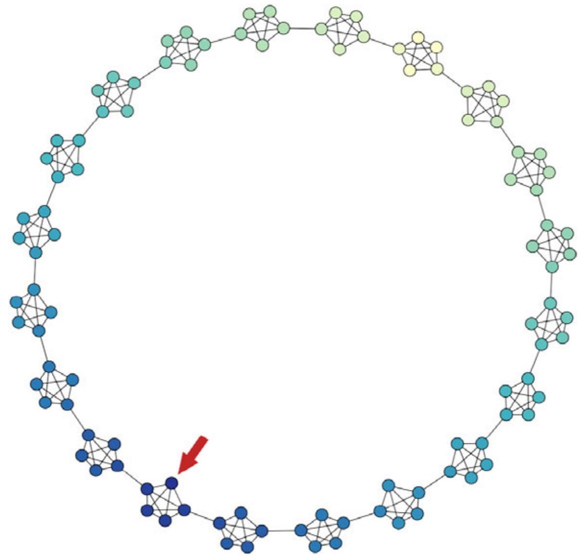

Figure 1. Connected caveman network

Another class of network is the small-world network, which is a network of global interaction, where the number of degrees of separation grows only logarithmically with the size of the network (Watts and Strogatz, 1998). Studies have identified two important elements of small-world networks: (1) bridges and (2) hubs.

First, a *bridge* is defined as "a tie between two nodes that would otherwise be much farther apart" (Granovetter, 1973). For example, consider small-world networks with bridges, such as an e-mail network. An e-mail user may frequently exchange messages with her nearby coworkers, but she may also get messages from or respond to individuals from any random place in the world. Such random connections beyond physical proximity are examples of bridges; their role was emphasized by Granovetter (1973). People often get more new information (useful in job searching, e.g.) from random contacts than from their friends and family members, because those random contacts act as bridges connecting diverse members from different, or often socially distant, subnetworks. In social relations, bridge-building mechanisms, such

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as conferences, parties, or social mobility, are often deliberately created to facilitate interactions among random contacts or strangers to cross the local boundaries of familiar worlds. Watts and Strogatz (1998) showed that a sufficiently small number of bridges can dramatically reduce the number of degrees of separation within an entire network. For example, Fleming, King, and Juda (2007) noted that inventor collaboration networks in Silicon Valley had been characterized as large-world networks for a long time, but a dramatic reduction in the number of degrees of separation occurred in the 1990s. This sudden reduction was attributed to the creation of bridges through the mobility of some scientists from one company to another.

The second element of a small-world network is the hub, whose role is illustrated in Albert, Jeong, and Barabási's (1999) research on the World Wide Web (WWW). Despite the vast number of documents on the WWW, two randomly chosen documents were estimated to be only 19 clicks away from each other. This small number of degrees of separation was attributable to the presence of hubs or extremely well-connected nodes. For example, the structure of the Twitter user network is characterized by hubs, the connectivity of which to other users is unrestricted. Kwak *et al.* (2010) showed that most Twitter users have only tens or hundreds of followers, but hubs, such as famous politicians, celebrities, or media companies, may have millions or tens of millions of followers.

Distribution sequence

The power of modern network theory is that researchers can infer dynamic properties from limited knowledge of topological properties. In particular, by analyzing the distribution sequence of a network, patterns in adoption dynamics can be inferred (Watts, 1999). To illustrate this point, consider again, the connected caveman network in Figure 1. Here, each local subnetwork has five members, all of whom are connected to one another. A pair of two adjacent local subnetworks is minimally connected such that only one link exists between them. Consider the simple diffusion process in which the focal individual with the arrow tries to spread information to every other member of the network step by step through the chains of neighborhoods. The information will first spread to the focal individual's four nearest neighbors, who will diffuse it to the second nearest neighbors at the second step. The number of the second nearest neighbors here is 2. At the third step, the information will diffuse to the third nearest neighbors, whose number is 8. In the connected caveman network, there is a pattern in which the number of new neighbors comes up at each step: 4, 2, 8, 2, 8, 2, 8, … (before the sequence runs out of new neighbors). At every two steps, the number of new neighbors comes up: 6, 10, 10, 10, … . The distribution sequence is a cumulative sequence of this new neighbor sequence, which expands at every two steps: 6, 16, 26, 36,.... The upshot is that the distribution sequence grows slowly or linearly in the connected caveman network.

Figure 2 shows that the pattern in the expansion of the distribution sequence is closely associated with degrees of separation. In general, the distribution sequence grows slowly in a network connected by a large number of degrees of separation. For example, the connected caveman network as a large-world network is linked by 100.7 degrees of separation in a network with a size of 1,000. If the focal individual tries to spread information to every other member of the network step by step through the chains of neighborhoods, it takes 200 steps to reach everyone else. On the other hand, when a network is characterized by a small number of degrees of separation (e.g., the reduction of degrees of separation to 4.7 and 17.4 degrees of separation in the two networks in Figure 2 is due to the presence of bridges), it takes very few steps to reach everyone else. As shown in Figure 2,

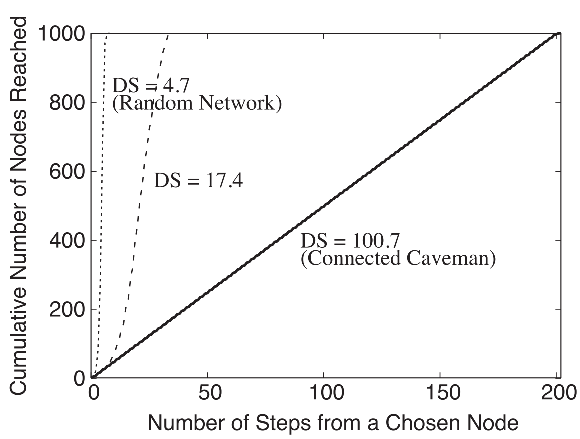

Figure 2. Degrees of separation and expansion of distribution sequence. *Note:* DS stands for a (characteristic) number of degrees of separation

the distribution sequences in the small-world networks expand exponentially. Since degrees of separation and the expansion of distribution sequences are closely associated, if one knows the degrees of separation for a network, he or she can predict how adoption dynamics will play out.

Clustering

Social networks are characterized by far higher levels of clustering compared to those in nonsocial networks, such as the Internet (router level) and connections between power stations (Newman and Park, 2003). Clustering represents the cliquishness of local subnetworks, or the extent to which friends of an individual are also friends of each other (Watts and Strogatz, 1998).

From a dynamic perspective, clustering is associated with smooth diffusion of a new network product or service at the initial stage. In general, the diffusion of network products or services is quite difficult to initiate, and they often end up being under-adopted (Rohlfs, 1974, 2001). This is primarily because the value of a network product or service increases as more and more customers adopt interoperable products or services, and because the value for early adopters is minimal when there are only a few adopters. This startup problem is more likely to happen in a poorly clustered network than in a highly clustered network (Choi, Kim, and Lee, 2010). Since clustering is the propensity for pairs of individuals to be connected if they share a mutual acquaintance, the adoption of a network product or service by one person in a highly clustered network naturally increases its value for other mutually connected individuals, thereby reducing the possibility of insufficient buildup of network benefits at the initial stage.

Propositions: the moderating role of degrees of separation

In the previous section, we briefly reviewed recent research on complex networks by focusing on three key topological properties: degrees of separation, distribution sequence, and clustering. In this section, we tie these notions to the existing theoretical framework to shed new light on the controversial issue of incumbency advantage and its relationship with incompatible entry. We propose that the number of degrees of separation moderates the strength of the relationship between an installed base and network effects, affecting incumbency advantage and the difficulty of incompatible entry.

Before introducing our propositions, we should make explicit the major assumptions underlying our adoption dynamics. First, we assume that individuals' propensities to adopt are constant within individuals over time, and that some customers decide to adopt a new service earlier than others as in previous studies (e.g., Abrahamson and Rosenkopf, 1997; Granovetter, 1978; Katz and Shapiro, 1985; Lee *et al.*, 2006). Second, each individual's willingness to adopt a service is primarily influenced by network effects or benefits. In particular, we consider the context in which these benefits arise from user–user interactions as is typical in social networking services such as Facebook and Twitter.

Given these assumptions, we claim that if a customer network is connected by a larger number of degrees of separation, incumbency advantage tends to be limited. In such a situation, incompatible entry is more likely. As discussed earlier, more degrees of separation in a network imply slow expansion of its distribution sequence. Under such conditions, information is likely to spread throughout the network at a slow rate. Similarly, we expect that the spread of network benefits (effects) throughout the network will also be slow. This, in turn, will increase the possibility of the existence of local subnetworks consisting of nonadopters. In such circumstances, an entrant with a new, incompatible service can gain a foothold by reaching these nonadopter subnetworks. Once nonadopters adopt the new service and influence other nonadopters to do likewise, the large number of degrees of separation combined with well-clustered local interactions will reinforce loyalty to the service since adopters' choices within the local subnetwork are compatible with one another. This development weakens the favorable effects of the installed base of the established service and limits its incumbency advantage. Thus, the relationship between the installed base and network effects may not be as strong (i.e., self-reinforcing) as was postulated in previous research.

In a network linked by a small number of degrees of separation, on the other hand, the distribution sequence expands exponentially. Under this condition, network benefits for an early mover's service will spread quickly throughout the network, self-reinforcing the early-mover's advantage and making nonadopter subnetworks vanish rapidly. Thus, a smaller number of degrees of separation strengthens the relationship between

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the installed base and network effects. In this scenario, winner-take-all dynamics are in effect for the established service, incumbency advantage becomes self-evident, and incompatible entry is more difficult.

In sum, we argue that incumbency advantage is limited in a network characterized by a larger number of degrees of separation, while in a network connected by fewer degrees of separation, the relationship between the installed base and network effects is strong, thereby increasing the durability of incumbency advantage. Thus, our central argument is that degrees of separation play a moderating role in the relationship between the installed base and network effects. The moderating effects offer one way to resolve the controversy regarding incumbency advantage and its relationship with incompatible entry. In the next section, a computational model with diverse customer networks is developed to demonstrate and confirm this claim.

BASIC MODEL

We now develop a computer simulation model to address the issue of incumbency advantage in circumstances of incompatible entry. Two key parameters in this analysis are degrees of separation and entry timing. The latter is of interest because it endogenously affects another key variable, the installed base. In the basic model, we consider the basic diffusion process of incompatible services when they are symmetrical in terms of quality, price, or other features. The only difference lies in the timing of service introduction. We deliberately assume this symmetry to demonstrate clearly the intertemporal influence of the installed base on network effects and adoption dynamics, while isolating these effects from other potential confounders. This symmetry condition will be relaxed later.

For simplicity, the model presented here is restricted to demand-side dynamics. In our model, each individual's willingness to adopt a service is represented by two factors: consumer reluctance to adopt the service and network effects. Reluctance can be regarded as a (psychological) cost, whereas the network effects represent customer benefits. When these benefits are greater than the user's reluctance, service adoption occurs.

In the basic model, only two incompatible services, A and B, are presented for simplicity. Since the two services are identical in quality and other features, individual i's willingness to use service j ($j = A, B$) at time t is expressed as

$$U_{ijt} = a\omega_{ij(t-1)} - R_i, \tag{1}$$

where a represents the importance of network effects, and R_i is user i's inherent reluctance to adopt any service. R_i is assumed to follow a normal distribution with $N(\mu,\sigma)$, which is based on the commonly used framework of adopter categories (Rogers, 1995).

The notation $\omega_{ij(t-1)}$ represents the proportion of user i's acquaintances who are using service j at time $t - 1$. More specifically,

$$\omega_{ij(t-1)} = \frac{\theta_{ij(t-1)}}{k_i},$$

where $\theta_{ij(t-1)}$ is the number of i's acquaintances who adopted service j at time $t-1$, and k_i is the total number of i's acquaintances. Thus, $0 \leq \omega_{ij(t-1)} \leq 1$. The formal representation here appears to reflect the network effects for a sparse network, in which each customer is connected to a small number of other customers. However, this specification can be extended to a complete network, in which everyone is connected to everyone else. Let n and λ denote the total number of customers and installed base, respectively. In a complete network, $k_i = n - 1$ because everyone is connected to everyone else. For the same reason, $\theta_{ij(t-1)} = \lambda_{j(t-1)}$. Given that n is large, $\omega_{ij(t-1)} = \lambda_{j(t-1)}/(n - 1) \approx \lambda_{j(t-1)}/n$, which is a typical representation of network effects in much of prior work.

Customer networks

In the basic model, a customer network is represented by the Watts-Strogatz (WS) model (Watts and Strogatz, 1998). This model has drawn substantial attention because of its relevance to social networks. One strength of this network model is that by tuning a single parameter β, we can generate networks with varying degrees of separation. Thus, by focusing on this tunable parameter, we can address our central question of whether degrees of separation affect the durability of incumbency advantage based on network effects.

The WS model was built upon a popular network model known as the one-dimensional lattice, which is coupled in geometrically regular ways. Consider the example on the left in Figure 3. The

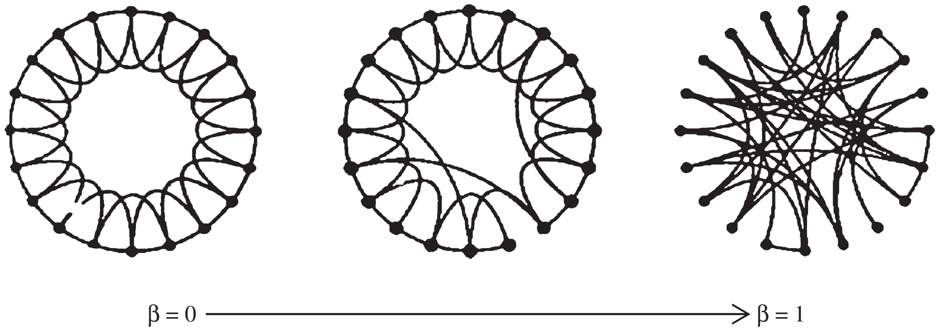

Figure 3. The Watts-Strogatz model. Source: Watts (1999: 68)

model starts with a regular network on a ring substrate with n nodes, where each node has exactly k nearest neighbors (in this example, $n = 20$ and $k = 4$). As in the connected caveman network, this regular network is an idealization of social interaction when it is completely constrained by physical distance. We can construct various types of networks in terms of degrees of separation by rewiring each link from a given node in the regular network to a randomly chosen node with probability β. The greater the value of β, the larger the number of random rewiring possibilities (bridges), and the smaller the number of degrees of separation (Watts, 1999).

Adoption rule for early adopters

There are two types of customers: early adopters and normal users. An early adopter adopts a service first at time step zero, when network benefits for the service are nonexistent. This decision stems from the early adopter's inherent positive valuation of the service, that is, $R_i < 0$. Initially, some early adopters adopt A, the first available service, with probability ρ, while other early adopters (with probability of $1 - \rho$) do not adopt it. The inactive early adopters will adopt service B when it is later introduced to the market and when the growth of service A does not preempt the entrant's service B. The inaction here is often associated with firm practices in reality. When a firm introduces a new product or service, it tends to focus on a limited market space partly because new product introduction involves high risk and partly because firm resources are usually limited. For example, Palm initially focused on Silicon Valley when it first introduced the Palm Pilot. In a similar vein, when Apple introduced the iPhone, the company initially focused on a few important markets, such as the United States and Europe, ignoring others. Early adopters in the ignored markets cannot adopt the product or service.

Adoption rule for normal users

Most customers are assumed to be normal users, whose inherent valuation of any service is not positive, unlike that of early adopters. That is, $R_i \geq 0$. Normal users will wait until the benefits from network effects exceed their negative valuation of the service. That is, the adoption rule is $U_{ijt} > 0$. This condition can be satisfied when their more enthusiastic friends (i.e., early adopters) use a service and build up network benefits, thereby influencing normal users. When service B competes with service A, a normal user's choice of service A depends on the size of $U_{iA(t-1)}$ in comparison with that of $U_{iB(t-1)}$. Between A and B, she chooses a service, of which $U_{ij(t-1)}$ is the largest.

Switching rule

After service B is introduced, adopters (both early adopters and normal users) can either stay with the previous service or switch to the new incompatible service at every period. For adoption and switching to service B, we again assume that $U_{iBt} > 0$. User i at period t compares the size of $U_{iA(t-1)}$ with that of $U_{iB(t-1)}$. Suppose that she adopted A at period $t - 1$. At period t, she switches to B if $U_{iA(t-1)} < U_{iB(t-1)}$. Otherwise, she stays with A. The switching rule for an adopter of B is similar to that for the adopter of A. This switching allows for the possibility that the bandwagon effect occurs with

Table 1. Parameter values for simulation

Parameter	Remarks	Range of parameter values analyzed
n	Number of individual customers	1,000
k	Average number of ties per node	10
ρ	Fraction of early adopters who adopt incumbent's service	0.5
μ	Mean for a normal distribution for customer heterogeneity (R_i)	90
σ	Standard deviation for a normal distribution for customer heterogeneity (R_i)	45
a[a]	Importance of network effects	400
β	Rewiring probability for the Watts-Strogatz network model	Figure 4: 0, 0.1, 1 Figure 5: 0.001, 0.002, 0.004, 0.008, 0.015, 0.03, 0.06, 0.125, 0.25, 0.5, 1.0 Figures 6 and 7: 0, 0.4 Figure 8: 0.015, 0.03, 0.06, 0.125, 0.25, 0.5, 1.0
Entry time	Time of entry of the latecomer	Figure 4: 10 Figure 5: 5, 15, 25, 35, 45 Figures 6 and 7: 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55
m_0	Initial number of nodes for a scale-free network	Figures 6 and 7: 3
m	Number of new links added per time step	Figures 6 and 7: 3
q	Service quality of the innovative entrant	Figure 8: 0, 10, 100, 200, 300, 500

[a] The value for a is exceptionally set at 1,000 for the complete network to avoid any possibility of under-adoption. The parameter value of 400 tuned for the sparse network is inappropriate for the complete network—it can often lead to under-adoption, which violates our assumption of the S-curve for the diffusion of services with broad appeal.

increasing participation in service B and declining participation in service A.

SIMULATION RESULTS

The results of the present simulation demonstrate how network properties affect the dynamics of incompatible entry and incumbency advantage. In particular, we numerically confirm the key claim that degrees of separation moderate the dynamic relationship between an installed base and network effects, thereby affecting incumbency advantage. Our analysis first focuses on competition between two incompatible services in the WS network model. Then, we extend our analysis to competition in various types of networks to establish the generality of our observations. All the parameter values for simulations are specified in Table 1. Here, the parameter values are tuned to generate the well-known S-curve, which is often observed in the diffusion of products that have broad appeal. Without proper tuning, network benefits at the initial stage may be too small to jump-start adoption dynamics. Although this under-adoption possibility does exist in reality, we choose to avoid it because it is rather trivial and uninteresting from a theoretical viewpoint.

Effects of degrees of separation

As a starting point, we show typical adoption dynamics on the WS network model. Recall that the key parameter β controls the number of bridges and degrees of separation in the network; the larger the value of β, the smaller the number of degrees of separation. As shown in Figure 4a, when $\beta = 1$ (a random network), or when the customer network is characterized by a small number of degrees of separation with abundant bridges, the incumbent quickly builds up its installed base. When the entrant introduces the new incompatible service at time step 10, very little room remains for the new service to gain a foothold. The incumbent corners the market in the steady state, which was quickly reached at time step 11. The steady state here is an equilibrium, where every customer will stay with the service she chose previously unless there is a large magnitude, external shock. When $\beta = 0.1$ (here, roughly 10% of all ties are bridges), adoption dynamics slow down somewhat, as shown in Figure 4b. However, in this particular

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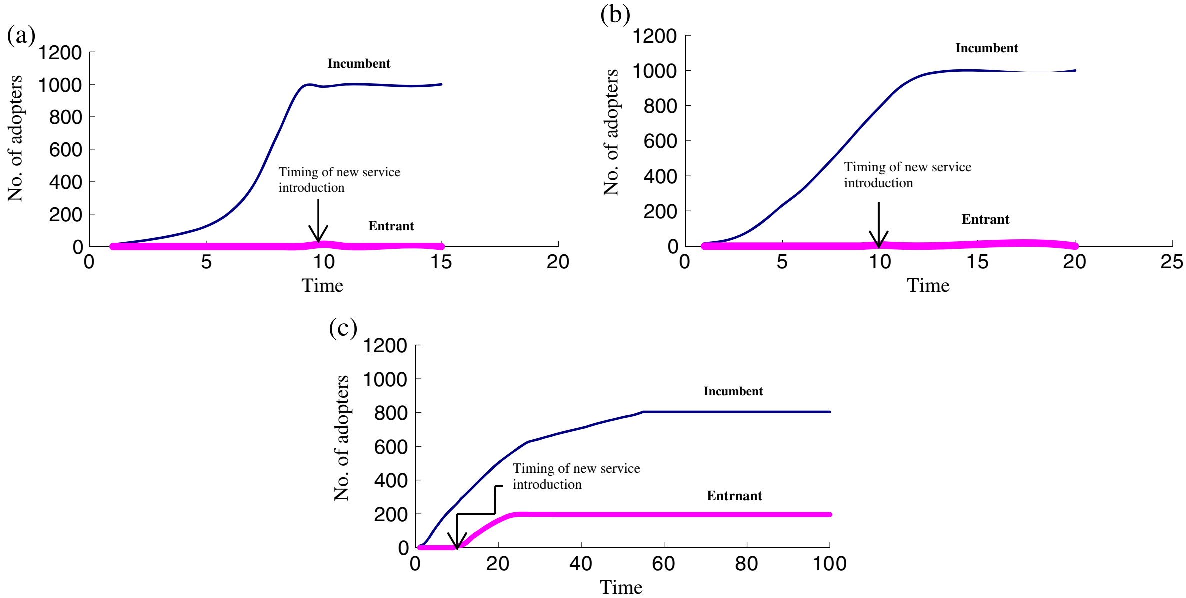

Figure 4. Typical adoption dynamics. (a) Typical simulation run for $\beta = 1$. (b) Typical simulation run for $\beta = 0.1$. (c) Typical simulation run for $\beta = 0$

scenario, the new incompatible service again fails to survive.

In contrast, when $\beta = 0$, or when the customer network is characterized by the largest possible number of degrees of separation with no bridges, the diffusion process is slowest. As shown in Figure 4c, 55 time steps were required for the diffusion process to reach 100 percent market penetration. When the new incompatible service enters at time step 10, the market has enough room for the entrant to establish a foothold and survive; at that point, only 23.7 percent of the population had adopted the incumbent's service, and many local subnetworks remained unfilled by users. In the steady state, the two incompatible services share the market. This coexistence is also observed when the new service is introduced at time step 45. At this point, 75.6 percent of the population has adopted the incumbent's service. All typical realizations together suggest that the survival of the entrant with a new, incompatible service depends on degrees of separation.

Variation in entry timing and degrees of separation

We conducted simulation experiments to investigate the effects of degrees of separation and entry timing on incompatible entry more systematically. To reduce statistical errors, each simulation was repeated 1,000 times. All data in Figure 5 were therefore averaged over 1,000 simulation runs. Figure 5 demonstrates the effects of timing on the probability of survival and the long-term market share of the entrant with a new incompatible service. The entrant's survival probability is calculated as follows. Out of the total 1,000 repeated simulations, we count the number of cases in which the entrant's service maintains a positive market share in the steady state. The survival probability is obtained by dividing this number by the total number of simulations. The results show that delayed timing makes it harder for the entrant to build its own installed base and to survive, shifting the curves in (a) and (b) to the left. However, timing affects outcomes only under certain conditions, such as when $0 \le \beta < 0.4$. When a network is characterized by a sufficiently small number of degrees of separation (e.g., $\beta \ge 0.4$), the simulation results show that the entrant has almost no chance of surviving regardless of entry timing. In contrast, the survival probability and the long-term market share of the entrant is always positive when a network is characterized by a larger number of degrees of separation (e.g., $\beta = 0.001$).

This result provides numerical evidence that the entrant's survival or market share depends on structural parameter β, which controls degrees

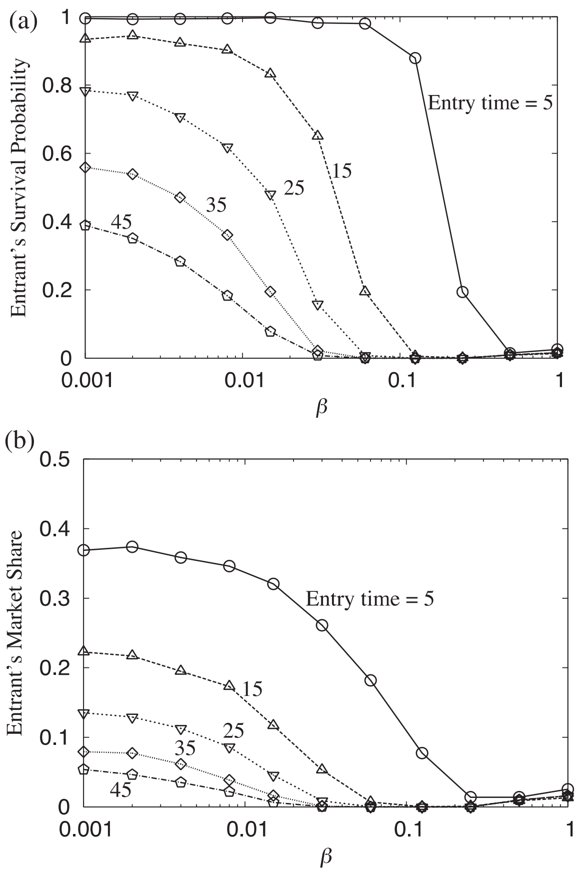

Figure 5. Effects of entry timing. (a) Entrant's survival probability in the steady state. (b) Entrant's market share in the steady state

of separation. In particular, the result displays a threshold-like behavior or regime change roughly around $\beta = 0.4$. Below this point, a shared market regime is in effect where the two incompatible services coexist. Above this point, the winner-take-all regime appears to come into effect, and incumbency advantage based on network effects completely blockades incompatible entry. We delve into this possibility later with the analysis of other types of networks.

Variation in incumbent's installed base

In the previous experiment, entry timing and the size of the incumbent's installed base are closely related, but they are not perfectly correlated. To isolate the effect of the installed base from other potential confounders, we also conduct another experiment, in which a new incompatible service is introduced after a controlled number of customers (the installed base) has already adopted the incumbent's service. The results of this experiment are not fully reported here because they are similar to those of the previous experiment: Incumbency advantage is stronger in networks with fewer degrees of separation, whereas incumbency advantage is weaker in networks with larger degrees of separation.

Variation in degrees of separation with a high level of clustering

In the WS model, degrees of separation and clustering covary. Therefore, it is possible that the key finding above may be confounded by clustering effects. To isolate the effects of degrees of separation from potential confounding effects, we modify the WS model by fixing the high level of clustering—that is, the WS model with no rewiring. We use this highly clustered network because high clustering is typical in real-world social networks (Girvan and Newman, 2002; Newman and Park, 2003). Then, we incrementally add new bridges by selecting two nodes at random and connecting them without removing any existing tie in the network—the removal of it serves to reduce the level of clustering in the WS model. We repeat this bridge-adding procedure to maintain the parameter value parity with β in the WS model. The numerical results show that the bridge effects are so dominant that even if we control for the level of clustering, the results look almost identical to those for the original WS model. The details of these results are presented in Figure 1 of Appendix.

Simulation experiments with various types of networks

In sum, the results of our simulations using the WS model suggest that network topology moderates the relationship between the installed base and network effects, which in turn, affects incumbency advantage. When a customer network is characterized by fewer degrees of separation, the incumbent's large installed base tends to strengthen its market position over time, leaving little room for the entrant with the incompatible service. When the customer network is characterized by a larger number of degrees of separation, the effects of the installed base are weakened. In such networks, the installed base as a global statistic is not a sufficient predictor of the durability of incumbency

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advantage. Some positive probability exists that the entrant will find local subnetworks of nonadopters if the timing of entry is not too late.

The analysis thus far has suggested that degrees of separation affect the difficulty of incompatible entry. To check the generality of this observation, we extend our analysis to complete and scale-free networks, which are also characterized by a small number of degrees of separation. Scale-free networks are generated according to the following procedure (Barabási and Albert, 1999). Initially, a network grows from m_0 nodes, all of which are connected to one another. At each time step, a new node is linked to m existing nodes according to the preferential attachment rule: existing node i will be connected to the new node with probability $\Pi(k_i) = k_i/\Sigma_j k_j$, where k_i denotes the total number of ties for node i. Note that i and j are elements from the set $\{1, 2, \ldots, n\}$. We let the network grow until the total number of nodes is n.

To reduce statistical errors, each simulation was repeated 1,000 times. As shown in Figure 6, the dynamics using scale-free and complete networks are similar to those using the WS networks with a substantial number of bridges (i.e., $\beta \geq 0.4$). The survival probability and the market share of the entrant are very close to zero regardless of the timing of entry chosen in the simulation.

All the networks described so far share one common topological property: a small number of degrees of separation. Does this topological property affect the dynamic properties of the networks? To answer this question, we first examine whether complete, scale-free, and the WS networks with abundant bridges generate winner-take-all behavior (Figure 7). In this experiment, all 1,000 simulations for these networks result in winner-take-all outcomes. On the other hand, in the WS networks characterized by a larger number of degrees of separation, the probability of the winner-take-all scenario is consistently smaller than 1. Although it is not reported here, connected caveman networks show similar behavior. The general observation is thus: Networks with a small number of degrees of separation generate winner-take-all behavior, whereas networks with a large number of degrees of separation do not.

To understand this regularity, we examine the relationship between network benefits (effects) and adoption rate by removing the complicating effects of competition on adoption dynamics. So, we set up the condition that only one service is available to attract customers in the market. We define the adoption rate as the number of new adopters per period. Although the results of this analysis are not fully reported here, we find that the dynamics of adoption rate are similar in complete, scale-free, and the WS networks with $\beta \geq 0.4$; the adoption rate in each network rapidly accelerates to a peak. This dramatic

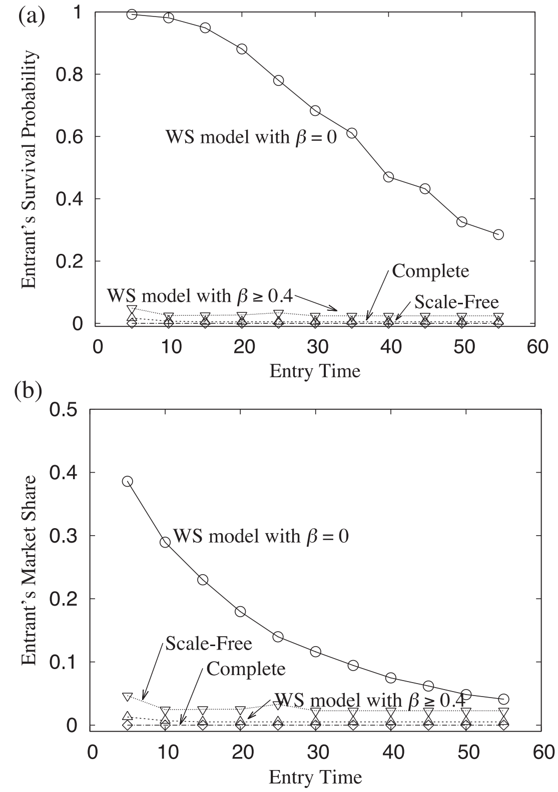

Figure 6. Simulation experiments in diverse networks. (a) Entrant's survival probability in the steady state. (b) Entrant's market share in the steady state

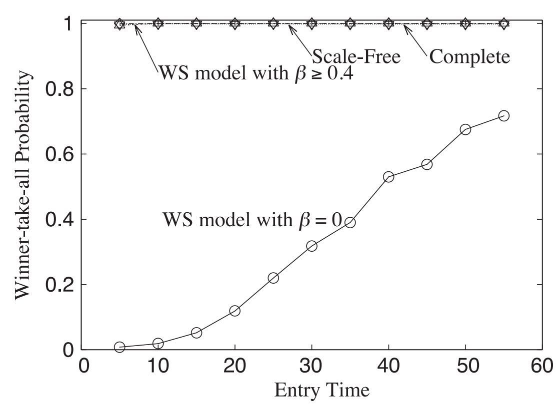

Figure 7. Winner-take-all behavior by network topology

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increase is consistent with the exponential expansion of distribution sequences for networks with fewer degrees of separation as discussed earlier. This acceleration of the adoption rate allows a first mover to enjoy a growing advantage over time. In a connected caveman network or in the WS network with smaller β, however, the adoption rate changes fairly gradually. This is consistent with the linearly expanding distribution sequences for networks with many degrees of separation. This implies that network effects increase gradually as a function of the adoption rate. Gradual dynamic behavior of this sort allows latecomers to build up their own customer bases and survive if the timing of entry is not too late, or more specifically, if some local subnetworks remain unfilled by adopters at all.

Simulations on bimodal distribution network

We conduct another sensitivity analysis with a bimodal distribution network model to overcome two limitations of the scale-free network model: (1) an unrealistically low clustering coefficient compared to those observed in real-world networks (Ravasz *et al.*, 2002); and (2) the lack of a control parameter that can be tuned through the middle ground to represent diverse networks with varying numbers of ties for hubs (Cohen, Havlin, and ben-Avraham, 2003). Here, the term *distribution* refers to the distribution of the number of ties per individual. In this model, parameter d controls the number of degrees of separation in a network. When d is large, hubs will appear and will be tied to many other individuals in the network. Then, the network will be characterized by fewer degrees of separation. In contrast, when d approaches zero, hubs will disappear, and the network will be characterized by the largest number of degrees of separation. The technical details of the simulations and their results are presented in Appendix. The key finding (Figure 2) is that when d is small, or when a network is characterized by a larger number of degrees of separation, there is some positive probability that a latecomer will be successful in building its own customer base and maintaining its positive market share in the steady state. As d increases, however, the latecomer's success probability and long-term market share both approach zero. The result of this analysis is also consistent with the key finding, the moderating role of degrees of separation in explaining the relationship between network effects and the installed base.

Effects of innovative entry

Schumpeter (1950: 84) conceptualized the notion of "creative destruction," which represents the possibility that entrants with innovation undermine the foundations of incumbents' very survival. Invoking this notion, some critics have recently argued that innovative entrants can match or sometimes sweep away incumbency advantage based on network effects (e.g., Farrell and Klemperer, 2007; Liebowitz, 2002; Liebowitz and Margolis, 2001; Schmalensee, 2000). As mentioned previously, AOL's dominant position in the IM market was at the heart of an antitrust policy debate at the turn of the new millennium, but the firm's incumbency advantage based on its installed base was not subsequently amplified. The Schumpeterian perspective could provide an alternative explanation for the limitations of incumbency advantage; the evolution of networking services with new features and functionality might have made existing ones obsolete.

In our model setup, we can incorporate the Schumpeterian perspective by allowing the entrant to improve the quality of its service through R&D activity. Here, we assume that the entrant only introduces a service with improved quality to match the incumbency advantage based on network effects. In the basic model with the WS network, we added a parameter q to represent the degree of improvement in quality compared to that of the incumbent. Thus, user i's willingness to adopt the entrant's service B is

$$U_{iBt} = a\omega_{iB(t-1)} - R_i + q.$$

An important question here is: Under what parameter condition (i.e., level of q) does innovative entry diminish moderating role of network topology? The simulation results in Figure 8 specify boundary conditions. When the entrant introduces an incompatible service of sufficiently greater quality relative to the existing one, it can not only gain a foothold in the market, but also displace the incumbent's existing service with a positive probability. Even when $\beta = 1$, the entrant has a positive market share in the steady state if $q \geq 200$. If $q = 500$, innovation effects completely wash out the moderating effects of network topology (β), and the entrant always drives out the incumbent. The results in the model with large q are rather consistent with the Schumpeterian argument outlined above.

In short, the role of degrees of separation becomes less significant when the entrant's service

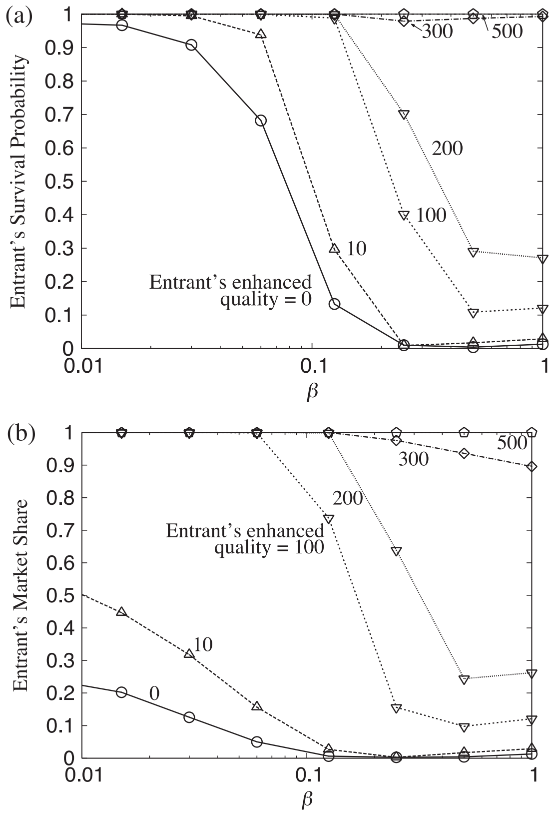

Figure 8. Effects of innovative entry. (a) Entrant's survival probability in the steady state. (b) Entrant's market share in the steady state

is of sufficiently high quality to outweigh the benefits of network effects. On the other hand, when the outcome of the entrant's innovation is small relative to the benefits of network effects, degrees of separation moderate the relationship between the installed base and network effects, thereby affecting incumbency advantage. We believe that the former case (major innovation) is less frequent than the latter (incremental innovation).

DISCUSSION

We developed a computational model to examine incumbency advantage in the face of incompatible entry. Our study shows that a measure of social distance, the degrees of separation in a customer network, determines boundary conditions for the durability of incumbency advantage. When customer networks are characterized by fewer degrees of separation (the presence of a sufficient number of hubs or social bridges), market dynamics tip toward the winner-take-all outcome, as has been typically shown in prior work on complete networks. In this case, incumbency advantage is strong, and early entry is crucial for firm survival. On the other hand, when a customer network is characterized by a larger number of degrees of separation, incumbency advantage is limited, and latecomers have a better chance of survival.

The findings of this study speak to the debate regarding network effects as a source of durable incumbency advantage. Theorizing the self-reinforcing relationship between the installed base and network effects, Arthur (1994) argued for strong incumbency advantage and emphasized the difficulty of incompatible entry. Critics responded to this argument by pinpointing that the incumbency advantage was not as durable as its advocates claimed it to be (Katz and Shapiro, 1994; Liebowitz and Margolis, 1990; Schmalensee, 2000), as evidenced by the history of technological competition. The resolution of the debate lies in identifying the conditions under which incumbency advantage based on network effects will or will not be durable. Much of prior work has taken the importance of the installed base for granted, implicitly assuming a complete network, which is characterized by the smallest number of degrees of separation. Here, the relationship between an installed base and the benefits of adoption (network effects) is self-reinforcing. Given that other possibilities are assumed away, the role of the network structure itself has been pushed to the background as if the prince of Denmark has been neglected in the discussion of *Hamlet*.

Assuming a context in which user benefits arise from user–user interactions (often called direct network effects), we show that the self-reinforcing process does not always develop. In particular, we view network structure as a moderator that strengthens or weakens the relationship between an installed base and network effects. When a network is characterized by a larger number of degrees of separation, the relationship between incumbency advantage and network effects weakens because its distribution sequence expands slowly within the network. Then, the benefits of adoption also spread slowly throughout the network. This is likely to allow a latecomer with an incompatible service to find local subnetworks consisting of nonadopters, for whom the benefits of adopting the established service will be relatively few because none of their friends adopt it. By reaching them, the latecomer can successfully gain a footing. Once some users

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adopt the new service and influence other users to do likewise, the large number of degrees of separation (or the predominance of local interactions) will encourage these adopters to remain loyal, since their choices within this local subnetwork are mutually compatible. Network structures for instant messaging and Facebook users appear to be characterized by a large number of degrees of separation. Most (ordinary) users have a moderate number of friends, and their user benefits come mostly from connections with their significant others. Furthermore, many, real-world networks consist of disconnected subnetworks (Fleming *et al.*, 2007; Onnela *et al.*, 2007). This type of network is less likely to confer strong enough incumbency advantage to shut out competition.

On the other hand, when a network is characterized by a small number of degrees of separation, the distribution sequence expands exponentially in complex chains of connections. That is, a sufficient number of bridges or hubs in a network can dramatically reduce the number of non-adopter subnetworks, rapidly increasing customer benefits (network effects) throughout every nook and cranny of a network. Then, the size of the installed base amplifies network effects throughout the network, self-reinforcing the early mover's advantage. In sum, in the scenario with fewer degrees of separation, the strong relationship between the installed base and network effects magnifies incumbency advantage, making incompatible entry difficult.

Our study offers directions for future research on both theoretical and empirical fronts. On the theoretical front, future research may relax some of the simplifying assumptions we imposed. For example, we focused on a positive feedback process on the demand side, while sidestepping the complexity of the supply side. In innovation races, some firms tend to be more successful than others, and winners tend to grow faster and drive out less successful firms over time (Lee, 2003; Lee *et al.*, 2010; Nelson and Winter, 1978; Phillips, 1971). Future research may also add this kind of positive feedback process on the supply side to enrich our understanding of the boundary conditions for incumbency advantage. Another challenging opportunity for ambitious modelers will be to develop an endogenous model wherein network evolution is affected by adoption dynamics. On the empirical front, there are also great research opportunities. We have identified an empirically observable variable, degrees of separation, which we propose to moderate the relationship between network effects and durability of incumbency advantage. Future researchers may empirically test this proposition.

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APPENDIX: ADDITIONAL ANALYSES

Model description

The bimodal distribution model represents social networks with two distinct modes, which are often observed in some networks of sexual contacts or social media (Cohen *et al.*, 2003). To construct a family of networks with varying numbers of ties

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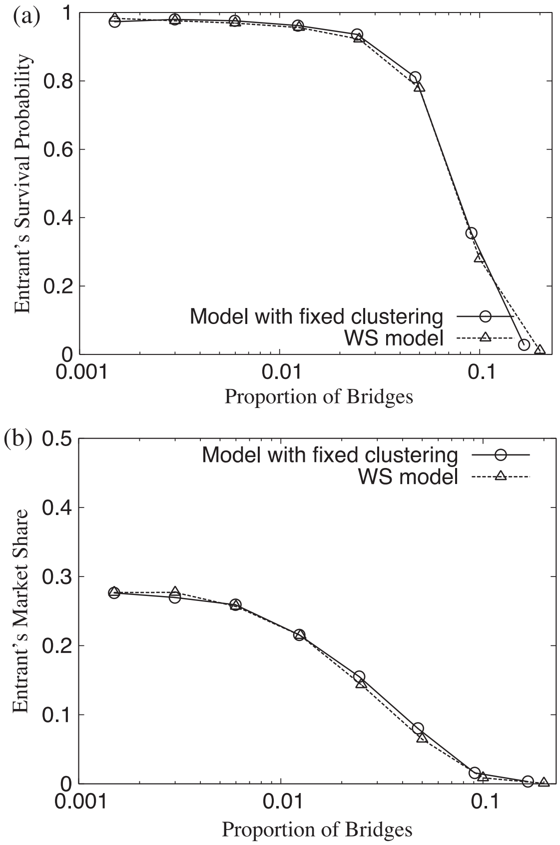

Figure 1. Effects of degrees of separation with fixed clustering. (a) Entrant's survival probability in the steady state. (b) Entrant's market share in the steady state

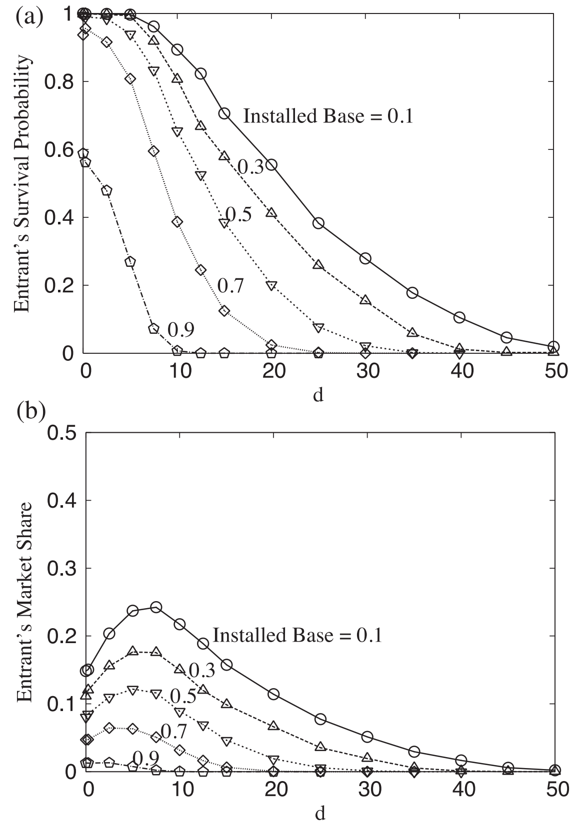

Figure 2. Simulation experiments in bimodal distribution networks. (a) Entrant's survival probability in the steady state. (b) Entrant's market share in the steady state. Note: Installed base here is represented by the number of customers as a fraction of the population size

for hubs, we start with a network characterized by high clustering. In this network, each individual has a number of ties to other individuals following a Gaussian distribution with μ_1. Then, we create a mixed distribution with another Gaussian distribution with μ_2. We let tunable parameter d control the distance between the two modes such that $d = \mu_2 - \mu_1$ (Cohen *et al.*, 2003). When d is large, hubs will be present in the network, and the network will be characterized by fewer degrees of separation. When d approaches zero, no hubs will be present, and the network will be characterized by larger degrees of separation. In conjunction with variation of d, we vary the size of the incumbent's installed base at time step 0 from 0.1 to 0.9.

The results here are consistent with our key finding, the moderating role of degrees of separation in explaining the relationship between network effects and the installed base. When d is small, there is some positive probability that a latecomer will be successful in building its own customer base and maintaining its positive market share in the steady state. As d increases, however, the latecomer's success probability and long-term market share both approach zero.

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