



The Role of Hubs in the Adoption Process

Author(s): Jacob Goldenberg, Sangman Han, Donald R. Lehmann and Jae Weon Hong

Source: *Journal of Marketing*, Vol. 73, No. 2 (Mar., 2009), pp. 1-13

Published by: [American Marketing Association](#)

Stable URL: <http://www.jstor.org/stable/20619007>

Accessed: 26-07-2015 12:12 UTC

REFERENCES

Linked references are available on JSTOR for this article:

http://www.jstor.org/stable/20619007?seq=1&cid=pdf-reference#references_tab_contents

You may need to log in to JSTOR to access the linked references.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at <http://www.jstor.org/page/info/about/policies/terms.jsp>

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.



American Marketing Association is collaborating with JSTOR to digitize, preserve and extend access to *Journal of Marketing*.

<http://www.jstor.org>

The Role of Hubs in the Adoption Process

The authors explore the role of hubs (people with an exceptionally large number of social ties) in diffusion and adoption. Using data on a large network with multiple adoptions, they identify two types of hubs—innovative and follower hubs. Contrary to recent arguments, hubs tend to adopt earlier in the diffusion process, even though they are not necessarily innovative. Although innovative hubs have a greater impact on the speed of the adoption process, follower hubs have a greater impact on market size (total number of adoptions). Importantly, a small sample of hubs offers accurate success versus failure predictions early in the diffusion process.

Keywords: social network, social hubs, influentials, opinion leaders, diffusion of innovation

Growth processes are important to marketing in general and to new product adoption in particular, in which the diffusion of an innovation is governed by, among other things, word of mouth. In social systems, growth processes are believed to be strongly influenced by people who have a large number of ties to other people. One example is the famous ride of Paul Revere who initiated (at least according to legend almost single-handedly) the American Revolution by riding through the night convincing people that they must start an armed resistance to the English army (Gladwell 2000). In the social network literature, such people are called influentials, opinion leaders, mavens, or hubs (Van den Bulte and Wuyts 2007), depending on the aspect of influence in question. Somewhat surprisingly, until recently these people have received relatively little attention in the marketing literature on innovation adoption. Furthermore, when the marketing literature addresses such people, the focus is typically not on how they influence the overall market; rather, the focus is on either assessing their influence on the people they are in direct contact with or identifying their characteristics.

Broadly speaking, influential people are believed to have three important traits: (1) They are convincing (maybe even charismatic), (2) they know a lot (i.e., are experts), and (3) they have a large number of social ties (i.e., they know a lot of people). In this article, we focus on the third trait, identifying social hubs—that is, people with a large number of ties to other people—and their influence on the overall process of innovation adoption. Somewhat contrary to

recent suggestions (Watts and Dodds 2007), we argue that social hubs adopt sooner than other people not because they are innovative but rather because they are exposed earlier to an innovation as a result of their multiple social links. We distinguish between innovator and follower hubs and show that the former influence mainly the speed of the adoption in a network and that the latter influence mainly the number of people who eventually adopt the innovation. We also show that a small sample of hubs can be used to make an early forecast of the entire diffusion process. Our analysis uses a relatively unique data set with a large number of diffusion processes on the Cyworld social networking site in Korea.

We begin by reviewing the literature and developing the hypotheses. Next, we examine how hubs influence the speed of the adoption process and the size of the total market. We also demonstrate how adoption by hubs provides an early prediction of the likely success of a new product.

Background

There is growing agreement among practitioners and academics on the fundamental role of social networks in the way information reaches consumers, channel members, and suppliers (Achrol and Kotler 1999; Iacobucci 1996; Rosen 2000; Van den Bulte and Wuyts 2007). Recent research has tied social network properties to the success of marketing actions, such as pricing or promotion strategies (Mayzlin 2002; Shi 2003). Much of the empirical research in this area has focused on relatively small networks (for a review, see Houston et al. 2004), tie strength (Brown and Reingen 1987; Rindfleisch and Moorman 2001), or social capital (Ronchetto, Hutt, and Reingen 1989).

Most diffusion models essentially treat the market as homogeneous, with the exception of some general adopter categories (e.g., innovators, main market, laggards). This is done for a practical reason: Networks and other more complex structures make modeling and estimation much more complicated. An attempt to examine the impact of network structure is in the area of “international diffusion.” Here, Putsis and colleagues (1997) examine how adoption in one country affects adoption in others, demonstrating the impor-

Jacob Goldenberg is Associate Professor of Marketing, School of Business Administration, Hebrew University of Jerusalem, and a visiting professor, Department of Marketing, Columbia University (e-mail: msgolden@huji.ac.il). Sangman Han is Professor of Marketing, School of Business Administration, Sungkyunkwan University, Korea (e-mail: smhan@skku.edu). Donald R. Lehmann is George E. Warren Professor of Business, Graduate School of Business, Columbia University (e-mail: drl2@columbia.edu). Jae Weon Hong is Assistant Professor of Marketing, School of Business Administration, Dongseo University, Korea (e-mail: jwhblue@empal.com). The authors thank Gita Johar and Christophe Van den Bulte for their helpful comments. They give special thanks to Rosanna Garcia for help in initial conceptualizations.

tance of communication within and across countries. Although this is an important direction for diffusion models, the size of the network is fairly small, and the analysis is at an aggregate level (i.e., the nodes are countries and not consumers). Similar work can be found in the business-to-business field. For example, Jones and Ritz (1991) suggest a two-stage diffusion process in which first an organization and then individuals within the organization adopt a product (for a different model, see Kim and Srivastava 1998).

Perhaps the best-known segmentation scheme in diffusion literature is the classification of consumers into adopter types (Rogers 1995). Recently, Van den Bulte and Joshi (2007) introduced a model using two adopter segments: influentials, who in turn affect another segment of imitators, and imitators themselves, whose own adoptions do not affect influentials. This two-segment structure with asymmetric influence is consistent with several studies in sociology and diffusion research (Goldenberg, Libai, and Muller 2002; Lehmann and Esteban-Bravo 2006).

Network Research in Marketing

A social network is defined by a set of actors and the relationships (ties) among them. Often, a person's importance can be inferred from his or her location in the network (Iacobucci 1996). Although it has been clear for a long time that network analysis is important for understanding growth processes (Rogers 1995) and that network analysis of field experiments is a promising direction for diffusion studies, relatively little has been done in this direction (Van den Bulte and Wuyts 2007).

One approach is to examine both the aggregate growth process and what happens at the individual level in a network. Reingen and Kernan (1986) demonstrate how such analysis can be carried out, emphasizing the roles of subgroups and referral flow in small social groups. Brown and Reingen (1987) examine an interpersonal network of a few hundred people and relate various roles and effects to tie strength. Broadly speaking, most research in marketing has focused either on the interaction within a link (e.g., Brown and Reingen 1987; Yang, Narayan, and Assael 2006) or on aggregate-level measures (e.g., Godes and Mayzlin 2004). Our research links individual measures to the aggregate diffusion process in a large population.

The Role of Key People

Research suggesting that a relatively small number of people have substantial influence on the opinions and decisions of the majority can be traced back at least 50 years (Katz and Lazarsfeld 1955). Opinion leaders are believed to have expertise in an area. In contrast, hubs (Barabassi 2003; Valente 1995) are people with a large number of social ties. Thus, although these two constructs are related, they are different. The literature on opinion leaders is relatively broad and has been examined in a variety of areas, including marketing, public opinion, health care, communication, education, agriculture, and epidemiology. There is wide agreement that opinion leaders can have a major impact on opinion formation and change and that a small group of influential opinion leaders may accelerate or block the adoption of a product.

Weimann (1991) suggests that influence is a combination of three personal and social factors: (1) the personification of certain values (or "who one is"), (2) competence ("what one knows"), and (3) strategic social location ("who one knows"). The first factor is associated mainly with personality traits, such as how persuasive a person is.

The second factor is associated with knowledge. Understanding product advantages and/or technical details is often important to people seeking advice. In general, opinion leaders and people who offer advice are more knowledgeable about and enduringly involved with the relevant product class (e.g., Richins and Root-Shaffar 1988; Venkatraman 1990). Myers and Robertson (1972) examine the "knowledgeability" of opinion leaders in 12 categories using 400 households in the Los Angeles area. The correlations between opinion leadership and various measures of knowledge and interest were moderate to high, ranging from a low of .37 (interest in household furnishing) to a high of .87 (knowledge about cosmetics and personal care).

A related concept is market mavenism (e.g., Coulter, Feick, and Price 2002; Engelland, Hopkins, and Larson 2001; Feick and Price 1987; Goldsmith, Flynn, and Goldsmith 2003; Steenkamp and Gielens 2003). Feick and Price (1987) emphasize the knowledge market mavens have about multiple products and places to shop (typically over a variety of categories) and their tendency to initiate discussions with consumers and offer information, partially because of their high involvement with the product class. As Coulter, Feick, and Price (2002) posit, because opinion leaders are involved in the product category and spend time shopping, they may also acquire more general marketplace expertise.

The third factor is associated with social capital (Burt 1997) and the type of social connectivity opinion leaders possess. In his work, Burt (1997) demonstrates how the value of social capital to a person is contingent on the number of people doing the same work. A person's main advantage consists of bridging structural holes, or the disconnections between different "nodes" in a network. Burt argues that people with high social capital stand at the crossroads of a large social organization and therefore have the option of bringing together otherwise disconnected people in the network. Because their contacts are more diverse, opinion leaders are more likely to be candidates for inclusion in new opportunities. In examining interpersonal influence in science, Schott (1987) suggests that a national community's influence is enhanced by its expertise (indicated by its number of Nobel laureates) and that the influence of one community on another is promoted by collegial and educational ties between them (indicated by coauthorships and student exchanges, respectively). Similarly, Weimann (1994) suggests that centrally positioned scholars (i.e., scientific opinion leaders) determine the direction of scientific progress because innovations adopted by central figures are more widely accepted by other members of the profession. Opinion leaders in a field tend to be interconnected, thus creating a powerful "invisible college" that dominates the adoption or the rejection of new scientific models, ideas, and methods. Keller and Barry (2003) discuss people who influence others and their relatively large numbers of social links. Similarly, Gladwell (2000) describes "connectors" as

people with a lot of influence on their surroundings, not because they are experts but rather because they are acquainted with an order of magnitude of more people than other people.

Richmond (1977) describes two major explanations for the informational superiority of opinion leaders over followers. The classic explanation is that opinion leaders have more exposure to the mass media than their followers (Katz and Lazarsfeld 1955). An alternative explanation is that opinion leaders acquire more information than nonopinion leaders from the same sources, including personal communications with large numbers of people who already have the relevant information.

In this article, we focus on the third factor, connectivity. Specifically, we examine people who are hubs—that is, those who have an exceptionally large number of social ties.

The Influence of Social Hubs

As we mentioned previously, a social hub is a person (node in a network) with a large number of ties. The influence of hubs on propagation in networks has been an object of study in the social network field since the work of Rapaport (1953). The network literature refers to propagation or diffusion as the transport from node to node of some quantity (e.g., information, opinion, disease). The spread of socially transmitted diseases is one example (for a modeling approach based on theoretical physics, see Newman 2002). Rapaport establishes the influence of network characteristics, such as the transitivity of node linking on disease propagation. Coleman, Katz, and Menzel (1966) assess dependence through a measure of “embeddedness” akin to the various measures of centrality that have evolved since the work of Bavelas (1948) and have been surveyed by Freeman (1978). Studies in this area include those of Valente (1995) and Rogers and Kincaid (1981). In Barabasi and Albert’s (1999) scale-free model, a few nodes dominate the connectivity of a network because of their extremely large number of ties. The number of ties (connections) is often termed the “degree of a node.” The distribution of people’s degrees often follows a power law, such that only a few people with the highest degree are considered the hubs. Barabasi and Albert also show that people remain connected even when a large number of links are broken (disconnected) because of the role of hubs. People with high degrees (hubs) should be central in any network. For example, in the case of the spread of a computer virus (Goldenberg et al. 2005), hubs are central in the infection process. The higher the degree of a person, the more neighbors they can affect.

Conversely, having many links does not necessarily make a person an innovator. A person who is both innovative and a hub is likely to adopt earlier. Even if a hub is not an innovator, however, there are likely to be several people who are connected to the hub who adopt the new product early. Such repeated exposure can lead to early adoption by the hub as well, not because of an innovative disposition but rather because of greater exposure (Goldenberg et al. 2005). Because hubs vary in their innovativeness, there may be different roles for and effects of innovative and less innovative hubs.

Recent work by Watts and Dodds (2007) based on simulation offers a different argument. More specifically, Watts and Dodds report that large cascades of influence can be driven not by hubs (they use the term *influentials*) but rather by a critical mass of easily influenced people. Nonetheless, their simulations found conditions in which hubs were disproportionately responsible for triggering large-scale “cascades” of influence. They emphasize that their results do not exclude the possibility that hubs can be important, and they suggest that examination of the role of hubs requires more careful specification and testing than it has received so far.

Recently, Trusov, Bodapati, and Bucklin (2008) examined an Internet social network. They found that the average person in a network is influenced by few other people and also influences only a few others. In addition, they observed strong heterogeneity, such that a small proportion of users participated in a substantial share of the influential dyads identified in the network. More precisely, they found some users whose total network impact was greater by a factor of eight more than most other members. However, they did not find that having many links (high degree) makes users influential per se. Although their research focuses on network activity rather than adoption processes over the network, it implies that hubs may indeed be important for diffusion.

Hypotheses

The main purpose of this article is to examine the role of hubs in diffusion in a natural setting. To consider both individual-level and aggregate behavior, data that include a large number of people (and nodes) and their adoption behavior for multiple products are required. This article follows the general perspective of examining an interpersonal network first used by Brown and Reingen (1987). However, we concentrate on the impact of people on the aggregate diffusion process rather than on individual adoption.

The previous discussion suggests that there is a small group of people who have a large number of social connections. Thus, a basic issue is to identify such hubs. The literature suggests that to some extent, opinion leaders are expert and innovative. However, there are no findings that connect expertise or innovativeness to social connectivity and having a large number of acquaintances.

Our first hypothesis pertains to the timing of adoption by hubs. The general two-stage model that has been widely adopted is that information moves from the media to opinion leaders and then from opinion leaders to their followers. We argue that hubs adopt first because of their greater exposure to an innovation, even if they are not innovators.

Consider a hub with a large number of ties (e.g., 500) who is not innovative and an innovator who has a smaller number of social ties (e.g., 25). Innovators require little exposure to make a decision to adopt. For this example, we assume that an innovator needs two product exposures and that the less innovative hub needs ten. However, because hubs are well connected, their number of indirect exposures to the new product is large even at early stages of the diffusion process. This can create a situation in which the social hub reaches his or her adoption threshold of ten exposures

before the innovator reaches his or her threshold of two. In other words, even hubs who are not innovative may be convinced at early stages of the process to adopt because of their large number of contacts and thus may be mistakenly identified as innovators on the basis of their time of adoption. Thus:

H₁: Social hubs are more likely to adopt at the early stages of a process.

There is no *a priori* reason to assume that all hubs share other traits. More specifically, there is no evidence that personal innovativeness is correlated with social connectivity (i.e., hubs can be innovative and connected or can simply be socially connected). Therefore, we distinguish between hubs who are genuine innovators (innovator hubs) and those who adopt early because of exposure to other adopters (follower hubs). Unlike Watts and Dodds (2007), who base the adoption threshold on the proportion of adoptions in a neighborhood necessary to trigger adoption, we use a fixed number as a threshold. Our reasoning is that social influence is proportional to the number of people a person knows who adopt rather than the percentage who adopt (exposures). If one person is connected to 10 people and another person is connected to 200, the adoption likelihood is more similar if each of them has 3 friends who adopted than when the first has 3 and the second has 60.

Given that hubs adopt early and because they have a large number of links that connect them to a large number of other people, their adoption should increase the speed of adoption in the period after they adopt (assuming the product adopted performs satisfactorily). We assume that the probability of a person's adoption (see Goldenberg, Libai, and Muller 2004) is as follows:

$$P = 1 - (1 - p)(1 - q)^{\alpha(t)},$$

where P is the probability that the person adopts, p is the effect of exposure to external forces (e.g., marketing efforts), q is the impact of word of mouth (network effects), and $\alpha(t)$ is the number of links to current adopters. The number of the adopters at time t would then be $E(P) \times [M - N(t)]$. This means that a person with a large number of links (e.g., 500) contributes much more to the adoption through interactions (word of mouth) than a person with a moderate number of links (e.g., 25). Even if we take the conservative view that social hubs are not more persuasive than other people or that they contact everyone to whom they are linked, more connections will be activated after these hubs adopt, resulting in a significant increase in the adoption rate. In addition, because innovator hubs adopt earlier than follower hubs, they have more time to influence the network. Thus:

H_{2a}: Hub adoption speeds up the overall adoption process.

H_{2b}: Innovator hub adoption has a larger correlation with speed of adoption than follower hub adoption.

Hubs are characterized by both in- and out-degree—that is, the number of people who convey information to them versus the number of people to whom they convey information. While in-degree should be primarily related to when a hub adopts (and is what leads hubs to adopt early), out-

degree should primarily determine the hub's influence on subsequent adoption. Therefore, we hypothesize the following:

H₃: All else being equal, the higher the relative out-degree of a hub, the greater is his or her impact on adoption.

We also hypothesize that social hubs influence market size. Social connections provide indirect information; thus, the larger the number of connections, the greater is the amount of information possessed. From a network point of view, access to diverse resources typically requires a person to be connected to diverse actors and subnetworks. This status can be obtained when both degree (number of ties) and betweenness (links to different groups) centralities are high. These centralities are typically correlated, partially because people with an extremely high degree have a higher probability of being connected to people in different social circles. In general, the extent to which someone has an information advantage depends on crossing structural holes, which means linking separate parts of the network (Burt 1992). In other words, being connected to many interconnected people creates an information advantage from collecting different bits of information sooner than the average network member (Van den Bulte and Wuyts 2007).

Even with the conservative assumption that social hubs are not more persuasive than the rest of the members in the network, hubs still have a large number of ties and, therefore, potentially more influence than others on people who are not necessarily connected to adopters. If a sufficiently large number of hubs adopt a product, it is more likely that the new product will be exposed to people who otherwise may not have been exposed to it. For example, if hubs are removed from a network, some people may not be exposed to the product sufficiently to trigger their adoption. Thus, we argue that adoption by hubs increases not only the speed of adoption but also market size.

Which type of hub adoption is more related to market size? Follower hubs are more similar to the population at large in terms of innovativeness. Therefore, their tastes and risk aversion are also likely to be more similar to the main market than those of innovative hubs, and thus they will be better predictors of overall market size. In addition, it seems logical that people place more trust in information from similar peers. Homophily, the degree to which pairs of people are similar in terms of certain attributes (Rogers 1995), is related to tie strength (Brown and Reingen 1987). Homophily fosters trust and reciprocity: It is easier to trust someone who is similar. Although homophily can become a barrier to innovation when different groups are involved, when it exists in a coherent market, it can enhance diffusion. Consistent with recent literature that examines the issue of main market versus early market adoption (see Goldenberg, Libai, and Muller 2002; Lehmann and Esteban-Bravo 2006; Van den Bulte and Joshi 2007), we argue that innovative hubs have more influence on the early market, while follower hubs have more influence on the main market. Because the main market is typically much larger, we also propose that follower hubs have a larger effect on the overall market size:

H_{4a}: Hub adoption increases the eventual size of a market.

H_{4b}: Follower hubs have a stronger relationship to market size than innovative hubs.

H₂ and H₄ would be in contradiction if adoption speed and market size were highly correlated. However, they are logically different. A process can be fast in either a large or a small market. Indeed, many fads have a rapid adoption rate among a small population, and many “really new” products require decades to reach their potential.

If hubs do not adopt a product soon after its introduction, this may impede adoption by those who are connected to the hubs. As a result, a higher adoption rate of hubs at the early stage of the diffusion process increases the probability of success of the product.¹ Thus:

H₅: Hub adoption at an early stage can be used to predict product success.

Data

To examine the role of hubs, data for which a large network is mapped are needed, and information about the timing of individual (node) adoption for multiple diffusion processes must be available. Fortunately, such a data set was available for this research. Specifically, we use data from a social network Web site in Korea—Cyworld.

Cyworld was founded in 1999. As of October 2006, there were approximately 22 million registered members (compared with approximately 100 million for MySpace). Many people consider Cyworld a part of everyday life for building relationships and sharing information about their life on their home page. The number of monthly unique visitors is approximately 20 million for Cyworld (<http://en.wikipedia.org/wiki/Cyworld>) versus 24.2 million a day for MySpace (Rosenbush 2005). The number of members in the database (measured every five months) increased from 2,492,036 in December 2003 to 12,685,214 in July 2005. Across this time, the number of hubs (we provide the measure of hubs subsequently) ranged from 1.28% to 3.30% (averaging 2.63%).

A key aspect of the service, at least for our purposes, allows people to customize their home pages by including documents, photos, and other “goodies” for free and to decorate their minihompy (personal home page) with paid items, such as virtual household items—furniture, electronics, wallpaper. (Cyworld generates money from these paid items and from advertising.) People can also adopt items such as pictures or video clips directly from the minihompies they visit (called “scraping” in Cyworld). In this study, we focus on this type of adoption, using data from December 2003 to July 2005.

Measures

The data contain information on scrap items—namely, item number, time of scrap, and creator ID of each item. By

¹Note that this is an “on-average” prediction. There are products that have been slow to take off, such as “ sleeper” movies (e.g., *Schindler’s List*, *Borat*), and thus their success due to early adopters was not apparent.

combining network information with information on scrap items, we track the diffusion process of items over the network. A common definition for connectedness in networks is the degree of each node (person in our case) (i.e., the number of links, or connections, to other nodes in the network). We use degree to identify hubs. We also separately measure out-degree as the number of other nodes ever visited by the hub and in-degree as the number of other nodes who have visited the hub. We adopt Trusov, Bodapati, and Bucklin’s (2008) approach and define links by activity (e.g., visits) and not by pointers, such as membership in address books. A link between two people in a social networking site (e.g., LinkedIn, Facebook) does not necessarily imply influence.

We define hubs as people with both in- and out-degrees that are larger than three standard deviations above the mean. (This definition is conservative and may weaken some of the effects because some hubs have a much higher degree.) We examined other definitions of hubs. For example, we assumed that total connections followed a geometric distribution and computed its mean and variance. We then selected as hubs people whose total connections were three standard deviations above the geometric mean. Because the results were essentially unchanged, we simply report the results for hubs who were three standard deviations above the arithmetic mean.

General descriptive statistics appear in Table 1. We divided the data into five periods and report the means, standard deviations, and medians for in-degree and out-degree by period. In- and out-degree are highly related; the correlation between in- and out-degree in each period is in the range of .90–.95.

Hubs can be innovative or not. We measured innovativeness on the basis of the adoption timing of each hub across multiple products. Specifically, for each product hubs adopted, we measured how many of their neighbors adopted it before them. The lower the number, the more “independent” they are (i.e., they adopt with less social influence).² We defined an innovative hub as one who adopted a particular product before anyone else in his or her neighborhood. This resulted in an average of 38.4% of the hubs being classified as innovative for each product. We classified all other hubs as followers. In other words, innovativeness is defined relative to others with whom a person is connected.³ We then averaged this 0–1 measure across all the products a particular person adopted and defined a hub as innovative if the average number of people who adopted before the hub was in the lowest 16% of all hubs (essentially capturing both innovators and early adopters in Rogers’s [1995] typology).

²An alternative measure can be constructed on the basis of the number of items adopted. However, such a measure would be confounded with both ability to pay and acquisitiveness. Thus, we assessed innovativeness on the basis of adoption within a social network.

³If hubs adopt earlier because of mass exposure rather than innovativeness, a population-based measure may classify people who are actually followers as innovators. Because we can examine whether a hub adopts before others in his or her own directly connected relationships, this measure seems most appropriate.

TABLE 1
Average Number of Connections

| Period | Total Membership | Arithmetic | | Geometric | | Mdn |
|--------|------------------|--------------------|-------|-----------|------|-----|
| | | M | SD | M | SD | |
| 1 | 2,492,036 | 13.76 ^a | 19.53 | 7.07 | 3.60 | 5 |
| | | 13.77 ^b | 18.79 | 7.14 | 3.56 | 6 |
| 2 | 5,941,393 | 19.92 | 25.32 | 10.92 | 3.64 | 11 |
| | | 20.04 | 24.73 | 10.40 | 3.79 | 11 |
| 3 | 8,675,741 | 21.43 | 25.12 | 12.53 | 3.48 | 13 |
| | | 21.59 | 24.54 | 11.74 | 3.69 | 14 |
| 4 | 10,264,533 | 20.66 | 25.82 | 12.59 | 3.34 | 12 |
| | | 20.90 | 24.92 | 10.98 | 3.77 | 13 |
| 5 | 12,685,214 | 17.34 | 24.64 | 12.14 | 3.05 | 8 |
| | | 17.71 | 23.18 | 7.80 | 4.23 | 8 |

^aOut-degree.

^bIn-degree.

This definition is imperfect. Consider two hubs, A and B. Assume that Hub A is connected mostly to people who adopt early and that Hub B is connected to people who adopt later. Even if the two hubs adopt an identical item at the same time, using our definition, Hub B is likely to be identified as an innovator hub simply because he or she is linked to followers. Therefore, we tested an alternative definition of innovative hubs in which innovativeness was determined relative to the entire population, such that any hub who adopted before 16% of the eventual adopters was labeled as innovative. The results based on this measure were less strong (e.g., in making early predictions).

Therefore, we use the neighborhood-based definition of innovativeness in the analyses. We concentrate our analyses on items that produced at least 400 scraps. This means that our analyses focused on 1067 items (of an unmanageable total of 7,500,488 for which we could establish posting dates). We defined a highly successful item as one that was in the top 30 items in terms of total adoption. Similarly, we defined a moderately (less) successful item as the 30 items whose total adoption was just below the average of the 1067 (i.e., ranked 534–563). This makes our tests more conservative than ones that compare the very best with the very worst. The average time for the entire adoption process (time until the last adoption) of the most successful items was 265 days, compared with 163 for the somewhat successful ones. This suggests that the diffusion process is rapid and that the appropriate time interval to analyze these data may be less than a day.

Results

Network Structure

In Figure 1, we present a sample network with links among 77 people from a panel selected using the snowball approach, which is widely used in mapping networks. The node in the center is connected to a relatively large number of other nodes. Almost any efficient information flow that is to cover the entire subnet passes through this local hub.

The entire network appears similar to a larger version of Figure 1, with many more hubs linked to a large number of other people. To demonstrate that the entire network has the

standard properties of networks, we computed the degree distribution (number of links for each node). In most cases, this distribution follows a power law, and such networks are termed “scale free” (Barabassi 2003). The degree distribution of connections appears in Figure 2. As is typical, the distribution is highly skewed; some nodes are hyperconnected, while the majority of nodes have only a few connections.

Adoption Timing

Most successful processes exhibit a takeoff, followed by intensive growth until a peak is reached, and then a decay to zero new adoptions. The growth pattern of scrap items posted over time appears in Figure 3; it follows a typical S-shaped diffusion pattern with a fast increase and saturation at the 400,000 level.

To test whether hubs adopt earlier than the rest of the population, we divided each diffusion process into five categories— $t_{5\%}$, $t_{16\%}$, $t_{30\%}$, $t_{50\%}$, and $t_{100\%}$, where $t_{5\%}$ is the time when the first 5% of total adoption occurs, $t_{16\%}$ is the time it takes for the first 16% of total adoption to occur, and so on. The adoption patterns of hubs and other people appear in Figure 4. Hub adoption has a tendency to decline slowly, while nonhub adoption increases over time. Thus, the concentration of hubs among first adopters is larger than among later adopters; on average, hubs adopt sooner than nonhubs ($t = 16.49$, $p < .0001$).

To examine the importance of neighborhood exposure, we compared hub and nonhub adoption. First, we randomly selected 100 hubs and 100 nonhubs. Second, we measured both the number of neighbors who adopted before the hubs and the proportion who did so for the 60 items we mentioned previously. The results appear in Table 2.

As we expected, hubs adopt earlier in their neighborhood in terms of the proportion of their neighbors who have adopted. However, consistent with our argument that the number of exposure drives adoption, hubs are not more innovative per se, because on average, they need 1.68 neighbors to adopt first versus only .61 for nonhubs. Thus, hubs appear to adopt early more because of their large number of connections (contacts) rather than their innate innovativeness (which, in one sense, is below average). This

FIGURE 1
A Sample of 77 People and How They Are Linked

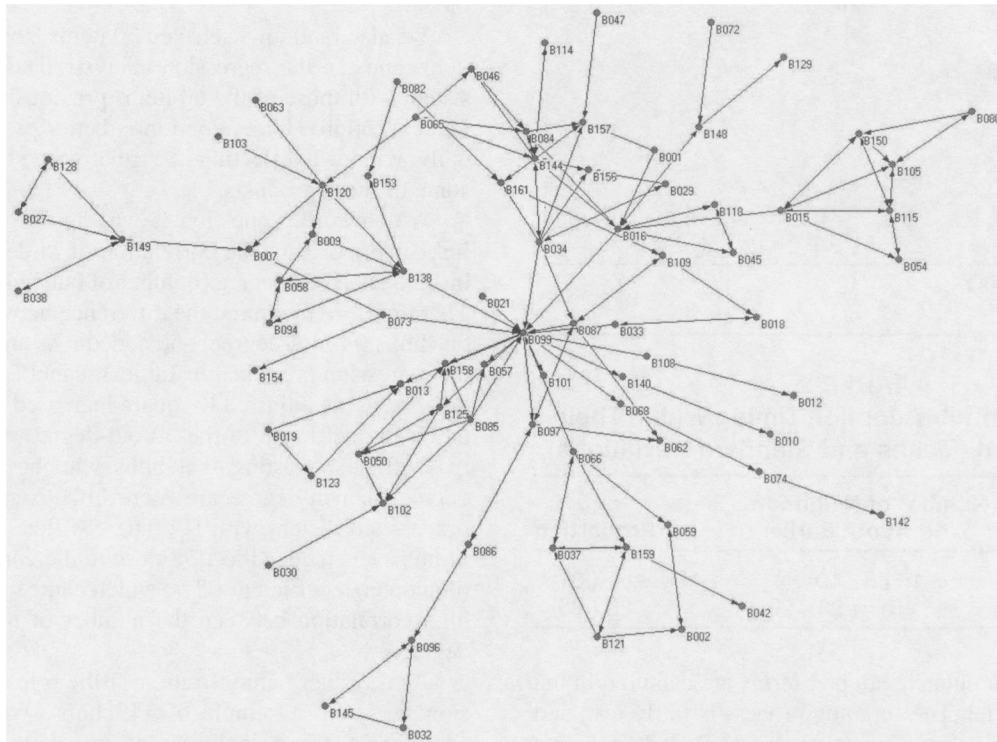
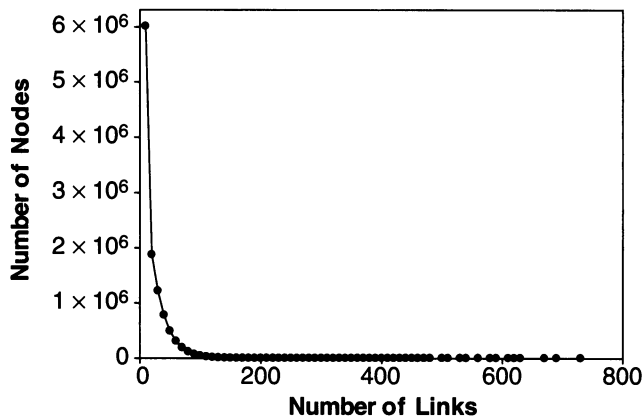
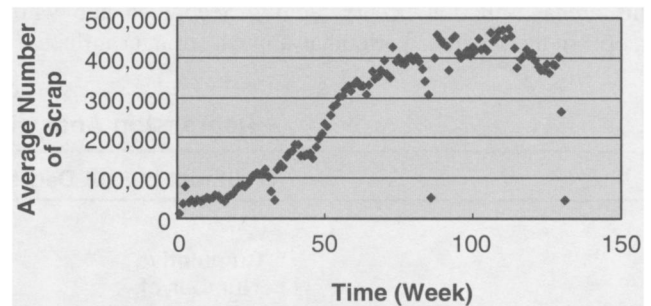


FIGURE 2
Degree Distribution of the Network



finding can explain the difference between our results and the simulation results in Watts and Dodds (2007). We argue that because people follow a number-of-exposures rule (rather than a proportion-of-households threshold rule), hubs adopt earlier because of the large number of connections they are exposed to sooner. An alternative explanation is that hubs adopt because of their innovativeness and not because of their connectivity; the reason for this result is

FIGURE 3
Number of Items Posted over Time



that hubs are connected to innovators and not to “ordinary” people. To demonstrate that hubs can adopt early in the process even if they are not innovative, we used an agent-based model. The results appear in the Appendix.

Hubs and Speed of the Adoption Process

To examine whether hubs speed up the adoption process, we selected the 30 most successful items and the first 30 just below average of the top 1067 in terms of eventual adoption. We performed a linear regression of the number of adopters at time t as a function of time, cumulative number of adopters at $t - 1$, the squared cumulative number of adopters at $t - 1$, and the number of new hubs adopting at

FIGURE 4
Percentage of Hub Adopters over Time

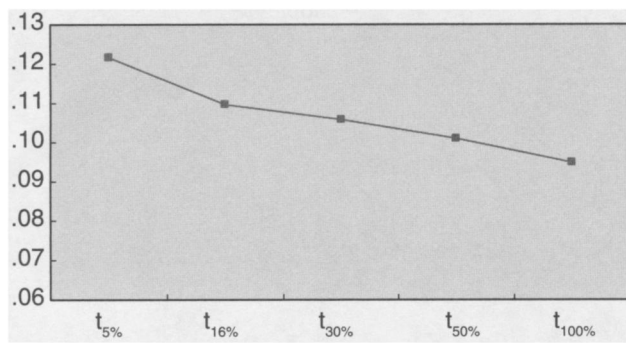


TABLE 2
Hub and Nonhub Adoption Timing Within Their Neighborhood (Means and Standard Deviations)

| | Number of Neighbors Who Adopt Earlier | Proportion |
|---------|---------------------------------------|------------|
| Hubs | 1.68 (2.10) | .01 (.01) |
| Nonhubs | .61 (.96) | .25 (.36) |

$t - 1$. The two cumulative adopter terms are captured in the Bass (1969) model. The scraping process is fairly fast, and the entire adoption process is often concluded in a few months, during which millions of people may adopt an item. We performed separate regressions using a period of a day, six hours, and two hours.

The results (Table 3, Panel A) are notable for several reasons. First, the model fits fairly well ($R^2 = .55-.75$), especially for the two-hour time interval, suggesting that in this arena, imitation occurs rapidly. Second, a hub who adopts in the previous period has a much stronger influence

than a typical adopter, suggesting that hubs are indeed critical to growth. Most important, the number of hubs adopting adds predictive power to cumulative adopters and cumulative adopters squared, the terms in the discrete Bass (1969) model.

We also randomly selected 30 items from the same 1067 items and ran the regression analysis. The results are consistent with those of the 60 items previously analyzed, with one exception. Here, adoption is better predicted using the daily window, reflecting the relatively slower growth of some of these products.

A noteworthy question is whether the direction of the links is important. The correlation of in-degree (number of in-links) and out-degree (number of out-links) is large ($>.9$). Therefore, we measured the difference between in-links and out-links (in-/out-degree) and added it as another variable to the regression presented in Table 3, Panel B. With the use of daily data, the adjusted R -square increased to .60. The standardized coefficient of the in-/out-degree variable was $-.60$ ($p < .01$), suggesting that hubs who have a higher out-degree than in-degree are more effective in speeding the process, consistent with H_3 . The coefficient of the number of hubs was reduced to .17, close to the cumulative number of adopters coefficient (.21), which can be explained by the high correlation between the number of hubs and in-/out-degree.

As a further demonstration of the role of hubs in diffusion, we took a sample of 113 hubs. We then observed adoption in their neighborhoods on a daily basis. Using the data up until the day of adoption, we estimated the Bass model and then forecasted the number of adoptions the day after the hub had adopted. We then compared the forecast with actual adoptions. In 106 of the 113 cases, adoptions the day after the hub adopted exceeded those predicted on the basis of adoptions up to that point (average = 1.79 versus .77, $p < .01$). Thus, at the neighborhood level, evidence suggests that hub adoption speeds overall adoption.

TABLE 3
Regression Analysis of Adoptions at Time t

| A: Without In-/Out-Degree (Standardized Coefficients) | | | | | | |
|---|-------|--|--|------------------------------------|----------------|----------------|
| Period | Time | Cumulative Number of Adopters at $t - 1$ | Square of Cumulative Number of Adopters at $t - 1$ | Number of Hubs Adopting at $t - 1$ | | Adjusted R^2 |
| Daily | -.02* | .21* | -.21* | .75* | | .59 |
| Six hours | -.02* | .21* | -.17* | .72* | | .55 |
| Two hours | -.01* | .12* | -.09* | .85* | | .75 |
| B: With In-/Out-Degree (Standardized Coefficients) | | | | | | |
| Period | Time | Cumulative Number of Adopters at $t - 1$ | Square of Cumulative Number of Adopters at $t - 1$ | Number of Hubs Adopting at $t - 1$ | In-/Out-Degree | Adjusted R^2 |
| Daily | -.02* | .21* | -.21* | .17* | -.60* | .60 |
| Six hours | -.02* | .22* | -.18* | .48* | -.25* | .55 |
| Two hours | -.01* | .12* | -.09* | .51* | -.37* | .77 |

*Significant at the .01 level.

To test the relative impact of innovative and noninnovative hubs on the speed of adoption, we examined (1) the time to saturation; (2) the time to the inflection point of cumulative adoption, $t^* = (p + q)^{-1} \ln(q/p)$; (3) the time to takeoff, $t^{**} = -(p + q)^{-1} \ln[2 + \sqrt{3(p/q)}]$; and (4) $t^* - t^{**}$. We adopted the last three measures from Van den Bulte (2000), and p and q are the Bass model coefficients that are estimated from the data. We examined the same 60 items (the 30 most successful and the 30 average ones). The range of time to saturation was 23 to 546 days (average = 214). We performed linear regressions with the four dependent variables and the number of innovative and follower hubs who had adopted as independent variables. Specifically, we measured the number of hubs who adopted in the first 23 days for $t_{16\%}$ and 55 days for $t_{50\%}$.

For all four measures, both innovative and follower hubs have a significant effect on the speed of the adoption process (Table 4), in support of H_{2a} . Moreover, an innovative hub's effect is more than twice that of a follower hub in most cases, in support of H_{2b} .

The data enable us to examine our hypotheses on an individual level. We isolated the hubs who were directly linked to neighbors and identified their time of adoption. The mean time of adoption of neighbors linked to innovator hubs was when 55% had adopted; in contrast, neighbors linked to follower hubs adopt at a mean time of 69% ($t = 35.1, p < .000$). This reinforces the argument that innovative hubs drive early adoption.

The Relation of Hub Adoption to Market Size

We have shown that hubs adopt early and speed up the adoption process. We now examine whether there is a corre-

lation between hub adoption and market size. Again, we analyzed the 30 most successful scraps and the first 30 just below average of the top 1067 in terms of eventual adoption. The total number of adopters (market size) in each process is the dependent variable. The results appear in Table 5, along with different time frames used as data in the regressions.

The R-square of the regression using the entire process is extremely high (.99), consistent with H_{4a} . Even after ten days, the number of hub adoptions is a good predictor ($R^2 = .88$) of eventual market size. Notably, follower hubs have approximately seven times the impact on market size than innovator hubs have, consistent with H_{4b} . Thus, in contrast to the results on speed of adoption, follower hubs appear to be more responsible for, or at least predictive of, the mass adoption of less innovative users and, therefore, total market size.

Predicting Product Success

To determine whether we can discriminate between the 30 highly and the 30 modestly successful products, we performed a logistic regression. The results appear in Table 6.

The classification table indicated 100% correct predictions. In this case, both innovative and follower hubs were significant predictors, and their coefficients were essentially equal. An explanation for these results is that innovator hubs initiate the process. Thus, if they choose not to adopt an item, they block the adoption process. In contrast, follower hubs give an item a second "push" in the main market, which is necessary for widespread adoption.

Overall, prediction is good, even when we use only hubs who adopted at the 5% adoption level, suggesting that

TABLE 4
Regression Analysis: Hub Adoption as Predictors of Adoption Timing

| Dependent Variable | Percentage Who Adopted | Innovative Hubs | Follower Hubs | Adjusted R ² |
|----------------------|------------------------|-----------------|---------------|-------------------------|
| Time to 16% | $t_{16\%}$ | -.54** | -.25** | .43 |
| Time to 50% | $t_{50\%}$ | -.63** | -.30** | .56 |
| t^* (time to peak) | $t_{16\%}$ | -.54** | -.24* | .42 |
| | $t_{50\%}$ | -.63** | -.30** | .56 |
| t^{**} | $t_{16\%}$ | -.31** | -.14** | .10 |
| (Time to takeoff) | $t_{50\%}$ | -.37** | -.24** | .20 |
| $t^* - t^{**}$ | $t_{16\%}$ | -.64** | -.28* | .59 |
| | $t_{50\%}$ | -.70** | -.27* | .63 |

*Significant at the .05 level.

**Significant at the .01 level.

TABLE 5
Regression of Market Size Versus Hub Adoptions (Standardized Coefficients)

| Time Frame | Innovative Hubs Coefficient | Follower Hubs Coefficient | Adjusted R ² |
|---------------------|-----------------------------|---------------------------|-------------------------|
| $t_{5\%}$ (10 days) | .11 (n.s.) | .83 (.00) | .88 |
| $t_{10\%}$ (17) | .15 (.00) | .85 (.00) | .99 |
| $t_{15\%}$ (23) | .12 (.00) | .89 (.00) | .99 |
| $t_{100\%}$ (214) | .14 (.00) | .86 (.00) | .99 |

Notes: The numbers in parentheses are significance levels. n.s. = not significant.

TABLE 6
Logistic Regressions: Large Versus Moderate Successes Versus Hub Adoption

| Data | Time of Hub Adopting | Innovator Hubs | Follower Hubs | Tenure | Correct Predictions |
|----------------------|---------------------------|----------------|---------------|-----------|---------------------|
| All sample hubs | t _{5%} (10 days) | .01 (.34) | .06 (.07) | .01 (.3) | 81.7% |
| All full-sample hubs | t _{10%} (17) | .01 (.34) | .06 (.03) | .01 (.03) | 80.0% |
| All full-sample hubs | t _{15%} (23) | .01 (.21) | .05 (.05) | .01 (.03) | 80.0% |
| Small sample hubs | t _{5%} (10) | 2.53 (.02) | 11.97 (.97) | | 70.0% |
| Small sample nonhubs | t _{5%} (10) | 1.25 (.29) | 11.64 (.97) | | 56.7% |

Notes: The numbers in parentheses are significance levels.

early forecasting based on hub adoption is potentially useful. (Again, when we added the cumulative number of adopters as a covariate, the results remained the same, and the coefficient of cumulative adopters was not significant.) In this analysis, adoption by follower hubs has a stronger link to whether a product eventually succeeds.

In the previous analysis, we used all the hubs in the analysis. This is not realistic in terms of managerial applications, because firms may not have access to such (complete) data. A more practical alternative would be to focus on a small sample of hubs (i.e., a hub panel), identifying them through market research (e.g., by examining their previous adoption history). To determine whether this approach is effective, we randomly selected a small sample of 280 hubs (139 innovative and 141 noninnovative). We then repeated the logistic regression to predict successes versus failures using this sample. As a stringent test, we examined whether this sample could yield successful predictions when only 5% of the market has adopted and compared it with the results based on an equal-sized sample of nonhubs. The results of both these regressions appear in Table 6.

Although the sample we chose is small compared with the overall population (only .006% of the hub population), 70% of the predictions were correct, close to the rate for the entire hub population. Furthermore, for the random sample of nonhubs, correct predictions occur in only 56.7% of the cases, close to chance and significantly worse than the results for the hubs.

Hub Correlates

It would be useful to identify hubs without collecting network data. To try to do this, we used two widely available demographic variables: age and gender. We also used two general characteristics of respondents: how long they had been members of Cyworld and how many items in total they had scraped (in essence, a measure of acquisitiveness). We compared a sample of 30,723 hubs with 289,001 nonhubs who adopted at least 1 of the 60 items we studied using logistic regression. Hub status is positively correlated with membership period and total number of acquisitions. The results (Table 7) also show that hubs are more likely to be male and young.

Discussion

This article examined diffusion in a well-documented social network. We find that hubs can be identified and classified into two types: innovator and follower hubs. Overall, social

TABLE 7
Predictors of Being a Hub (Dependent Variable: Hub = 1, Nonhub = 0)

| Parameter | Estimate | Error | p-Value |
|-------------------------|----------|-------|---------|
| Intercept | -1.011 | .026 | .000 |
| Age | -.087 | .001 | .000 |
| Gender (male) | .415 | .013 | .000 |
| Membership period | .001 | .000 | .000 |
| Total of items acquired | .016 | .001 | .000 |

hubs appear to adopt earlier because of their larger number of connections rather than innate innovativeness.

Adoption by hubs speeds up the growth process and directly influences eventual market size. Innovator hubs influence mainly the speed of adoption, while follower hubs mainly influence market size. Moreover, hub adoption serves as a useful predictor of eventual product success; even a small sample of hubs can give reasonable predictions in very early stages. The implication of the last finding is that a firm can collect a sample of hubs and use this panel as a "test tube" for early predictions. This is important because, in general, there is little indication of whether and when a takeoff should be expected (for exceptions, see Garber et al. 2004; Golder and Tellis 1997). Note that this approach should be performed with "minimal invasion." For example, the effects of "mere questions" (Levav and Fitzsimons 2006) can contaminate the results by influencing hub behavior.

An application of the findings, other than as an aid to forecasting, is to buzz marketing. If social hubs can be identified (and privacy concerns overcome), they could be an efficient target for word-of-mouth campaigns, leading to both faster growth and increased market size.

A limitation of this study is that the nature of the items is relatively unique and may not generalize to the entire span of innovations and new products. Although the network itself and adoption process are both close in structure and dynamic to typical network and adoption processes, replication is called for in different contexts. Specifically, it is important to test the influence of hubs on the dynamics of adoption with more "classic" products, which defuse more slowly, though mapping the relevant network may be a serious problem.

Because data sets on large networks with multiple processes are difficult to construct, other approaches, such as tracing hubs and examining their behavior in a longitudinal study, may be a useful avenue for further research. Another

direction for research is to develop methods to identify hubs in a network on the basis of penetration and other data (i.e., general descriptors). In addition, accounting for characteristics of the items themselves (as either fixed or random effects) is worth pursuing.

The value of a customer to the firm is more than the sum of his or her purchases; it also includes the effect of some people (i.e., hubs) on others. Such influentials have substantially greater value than has previously been realized. We hope that the results herein encourage work to better understand the motivations, behaviors, and impacts of well-connected people in their social structures.

Appendix

A way to study dynamics in a system is to use agent-based modeling. Interactions between agents (in our case, adopters) lead to distinct collective phenomena, whose so-called emergent properties can be described at the aggregate level (Goldenberg, Libai, and Muller 2004; Lusch and Tay 2004).

Here, each agent is a potential adopter of the innovation. The probability that a given agent adopts an innovation at time t , given that he or she has not yet adopted it, depends on two factors: external marketing (e.g., advertising), represented by parameter p , and internal social interaction (word of mouth), represented by parameter q .

Given that $k_i(t-1)$ is the number of agent i 's neighbors who adopted at time $t-1$ and that $f_i(t)$ is the probability that agent i will adopt at time t , Garber and colleagues (2004) use the following specific form of f :

$$f_i(t) = 1 - [(1-p)(1-q)^{k_i(t-1)}].$$

We sampled one representative cluster (subnetwork) in the data and generated an agent-based model. We use the model as an adoption threshold; when the number of neighbors exceeds a threshold, the agent adopts. Specifically, we implemented the number of nodes (equivalent to adopters in the data) and their tie distribution in a net-logo software framework. The hubs are defined by the data themselves. Thus, contrary to most uses of agent-based modeling, here the simulation is tied to the sampled network.

Some limited empirical and experimental evidence supports the assumption that people follow threshold rules when making decisions in the presence of social influence. We sampled 2655 members from the network of adopters of the 60 items we studied, using a snowball sampling approach; each identified adopter was a starting point from which to identify associates in the network. We based the distribution of degrees in the simulation on these numbers. To define the adoption threshold for each node (the number of exposures through linked adopters required to generate adoption), we used the threshold distribution in the subnetwork and randomly assigned thresholds to the nodes. In addition, we kept the same proportion of hubs (2.63%) who were among the 2655 members in the analysis. To start this process, seeding (assigning nodes that adopt at t_0) is required. We used seed ratios of .1%~3%, similar to the range of the values of p found in the Bass model.

The average adoption time for hubs and regular nodes in the simulation appears in Table A1. With the exception of the lowest seeding values, hubs were more likely to adopt and, when they did adopt, to do so earlier.

TABLE A1
Simulated Adoption Pattern

| Seed Ratio (%) | Percentage Adopting | Average Adoption Percentage | | t | p -Value | Average Adoption Time | | t | p -Value |
|----------------|---------------------|-----------------------------|--------|------|------------|-----------------------|--------|-----|------------|
| | | Hub | Nonhub | | | Hub | Nonhub | | |
| .1 | 13.6 | 14.4 | 10.2 | 1.4 | .167 | 3.8 | 4.1 | .8 | .414 |
| .3 | 6.8 | 9.8 | 6.7 | 2.5 | .017 | 1.8 | 2.4 | 3.6 | .001 |
| .5 | 15.6 | 17.3 | 15.6 | 2.6 | .013 | 3.0 | 3.6 | 2.5 | .015 |
| .7 | 14.2 | 22.8 | 14.0 | 10.5 | .000 | 2.3 | 2.9 | 4.6 | .000 |
| 1.0 | 22.3 | 26.3 | 22.2 | 4.8 | .000 | 2.1 | 2.8 | 5.0 | .000 |
| 1.5 | 20.9 | 30.0 | 20.7 | 21.2 | .000 | 1.9 | 2.4 | 5.6 | .000 |
| 2.0 | 14.4 | 23.7 | 14.2 | 9.6 | .000 | 1.8 | 2.1 | 4.6 | .000 |
| 2.5 | 21.9 | 27.7 | 21.8 | 8.6 | .000 | 1.9 | 2.5 | 5.1 | .000 |
| 3.0 | 22.3 | 30.2 | 22.0 | 12.1 | .000 | 1.8 | 2.2 | 6.0 | .000 |

REFERENCES

- Achrol, Ravi S. and Philip Kotler (1999), "Marketing in the Network Economy," *Journal of Marketing*, 63 (Special Issue), 146-63.
- Barabassi, Alber-Laszio (2003), *Linked*. New York: Plume/Penguin Books.
- and Reka Albert (1999), "Emergence of Scaling in Random Networks," *Science*, 286 (5439), 509-512.
- Bass, Frank M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science*, 15 (5), 215-27.
- Bavelas, A. (1948), "A Mathematical Model for Group Structure," *Human Organizations*, 7 (1), 16-30.
- Brown, Jacqueline Johnson and Peter H. Reingen (1987), "Social Ties and Word-of-Mouth Referral Behavior," *Journal of Consumer Research*, 14 (3), 350-62.
- Burt, Ronald S. (1992), *Structural Holes: The Social Structure of Competition*. New York: Harvard University Press.
- (1997), "The Contingent Value of Social Capital," *Administrative Science Quarterly*, 42 (2), 339-58.
- Coleman, James S., Elihu Katz, and Herbert Menzel (1966), *Medical Innovation: A Diffusion Study*. New York: Bobbs-Merrill.
- Coulter, Robin A., Lawrence F. Feick, and Linda L. Price (2002), "Changing Faces: Cosmetics Opinion Leadership Among

- Women in the New Hungary," *European Journal of Marketing*, 36 (11–12), 127–38.
- Engelland, Brian T., Christopher D. Hopkins, and Dee Ann Larson (2001), "Market Mavenship as an Influencer of Service Quality Evaluation," *Journal of Marketing Theory and Practice*, 9 (4), 15–26.
- Feick, Lawrence F. and Linda L. Price (1987), "The Market Maven: A Diffuser of Marketplace Information," *Journal of Marketing*, 51 (1), 83–97.
- Freeman, Linton C. (1978), "Centrality in Social Networks: Conceptual Clarification," *Social Networks*, 1 (3), 215–39.
- Garber, Tal, Jacob Goldenberg, Libai Barak, and Eitan Muller (2004), "From Density to Destiny: Using Spatial Analysis for Early Prediction of New Product Success," *Marketing Science*, 23 (3), 419–29.
- Gladwell, Malcolm (2000), *The Tipping Point*. New York: Little, Brown and Company.
- Godes, David and Dina Mayzlin (2004), "Using Online Conversations to Study Word-of-Mouth Communication," *Marketing Science*, 23 (4), 545–61.
- Goldenberg, Jacob, Barak Libai, and Eitan Muller (2002), "Riding the Saddle, How Cross-Market Communications Can Create a Major Slump in Sales," *Journal of Marketing*, 66 (April), 1–16.
- , ———, and ——— (2004), "Complex, yet Simple: Cellular Automata as an Enabling Technology in Marketing Strategy Research," in *Assessing Marketing Strategy Performance*, Christine Moorman and Donald R. Lehmann, eds. Cambridge, MA: Marketing Science Institute, 229–46.
- , Shavit Yuval, Shir Eran, and Solomon Sorin (2005), "Distributive Immunization of Networks Against Viruses Using the 'Honey Pots' Architecture," *Nature Physics*, 1 (December), 184–88.
- Golder, N. Peter and Gerard J. Tellis (1997), "Will It Ever Fly? Modeling the Takeoff of Really New Consumer Durables," *Marketing Science*, 16 (3), 256–70.
- Goldsmith, Ronald E., Leisa R. Flynn, and Elizabeth B. Goldsmith (2003), "Innovative Consumers and Market Mavens," *Journal of Marketing Theory and Practice*, 11 (4), 54–65.
- Houston, Mark, Mike Hutt, Christine Moorman, Peter Reingen, Aric Rindfleisch, Vanitha Swaminathan, and Beth Walker (2004), "Marketing Networks and Firm Performance," in *Assessing Marketing Strategy Performance*, Christine Moorman and Donald R. Lehmann, eds. Cambridge, MA: Marketing Science Institute, 227–68.
- Iacobucci, Dawn (1996), *Networks in Marketing*. Thousand Oaks, CA: Sage Publications.
- Jones, J. Morgan and Christopher J. Ritz (1991), "Incorporating Distribution into New Product Diffusion Models," *International Journal of Research in Marketing*, 8 (2), 91–113.
- Katz, Elihu and Paul F. Lazarsfeld (1955), *Personal influence: The Part Played by People in the Flow of Mass Communications*. Glencoe, IL: The Free Press.
- Keller, Ed and Jon Barry (2003), *The Influentials: One American in Ten Tells the Other Nine How to Vote, Where to Eat, and What to Buy*. New York: The Free Press.
- Kim, Namwoon and Rajendra K. Srivastava (1998), "Managing Intraorganizational Diffusion of Technological Innovations," *Industrial Marketing Management*, 27 (3), 229–46.
- Lehmann, Donald R. and Mercedes Estelban-Bravo (2006), "When Giving Some Away Makes Sense to Jump Start the Diffusion Process," *Marketing Letters*, 17 (December), 243–54.
- Levav, Jonathan and Gavan J. Fitzsimons (2006), "When Questions Change Behavior: The Role of Ease of Representation," *Psychological Science*, 17 (3), 207–213.
- Lusch, Robert F. and Nicholas S.P. Tay (2004), "Agent-Based Modeling: Gaining Insights into Firm and Industry Performance," in *Assessing Marketing Strategy Performance*, Christine Moorman and Donald R. Lehmann, eds. Cambridge, MA: Marketing Science Institute, 212–27.
- Mayzlin, Dina (2002), "The Influence of Social Networks on the Effectiveness of Promotional Strategies," working paper, School of Management, Yale University.
- Myers, James H. and Thomas S. Robertson (1972), "Dimensions of Opinion Leadership," *Journal of Marketing Research*, 9 (February), 41–46.
- Newman, Mark E.J. (2002), "The Spread of Epidemic Disease on Networks," *Physics Review*, E66, 16128.
- Puttsis, William P., Seidhar Balasubramanian, Eduard H. Kaplan, and Subrata K. Sen (1997), "Mixing Behavior in Cross-Country Diffusion," *Marketing Science*, 16 (4), 354–69.
- Rapaport, A. (1953), "Spread of Information Through a Population with Sociostructural Bias: Assumption of Transitivity," *Bulletin of Mathematical Biophysics*, 15, 523–33.
- Reingen, Peter H. and Jerome B. Kernan (1986), "Analysis of Referral Networks in Marketing: Methods and Illustration," *Journal of Marketing Research*, 23 (November), 370–79.
- Richins, Marsha L. and Teri Root-Shaffer (1988), "The Role of Involvement and Opinion Leadership in Consumer Word-of-Mouth: An Implicit Model Made Explicit," in *Advances in Consumer Research*, Vol. 15, Michael Houston, ed. Provo, UT: Association for Consumer Research, 32–36.
- Richmond, Virginia P. (1977), "The Relationship Between Opinion Leadership and Information Acquisition," *Human Communication Research*, 4 (1), 38–43.
- Rindfleisch, Aric and Christine Moorman (2001), "The Acquisition and Utilization of Information in New Product Alliances: A Strength-of-Ties Perspective," *Journal of Marketing*, 65 (April), 1–18.
- Rogers, Everett M. (1995), "New Product Adoption and Diffusion," *Journal of Consumer Research*, 2 (4), 290–302.
- and D.L. Kincaid (1981), *Communication Networks: A New Paradigm in Research*. New York: The Free Press.
- Ronchetto, John R., Jr., Michael D. Hutt, and Peter H. Reingen (1989), "Embedded Influence Patterns in Organizational Buying Systems," *Journal of Marketing*, 53 (October), 51–62.
- Rosen, Emmanuel (2000), *The Anatomy of Buzz: How to Create Word-of-Mouth Marketing*. New York: Doubleday Currency.
- Rosenbush, Steve (2005), "Users Crowd into MySpace," *BusinessWeek*, (November 15), (accessed December 2, 2008), [available at http://www.businessweek.com/technology/content/nov2005/tc20051115_908925.htm].
- Schott, Thomas (1987), "International Influence in Science: Mathematicians in Denmark and Israel," *Social Network*, 9 (1), 351–75.
- Shi, Mengze (2003), "Social Network-Based Discriminatory Pricing Strategy," *Marketing Letters*, 14 (4), 239–56.
- Steenkamp, Jan-Benedict E.M. and Katrijn Gielens (2003), "Consumer and Market Drivers of the Trial Probability of New Consumer Packaged Goods," *Journal of Consumer Research*, 30 (3), 368–84.
- Trusov, Michael, Anand V. Bodapati, and Randolph E. Bucklin (2008), "Determining Influential Users in Internet Social Networks," working paper, Robert H. Smith School of Business, University of Maryland.
- Valente, Thomas W. (1995), *Network Models of the Diffusion of Innovations*. Cresskill, NJ: Hampton Press.
- Van den Bulte, Christophe (2000), "New Product Diffusion Accelerations Measurement and Analysis," *Marketing Science*, 19 (4), 366–80.
- and Yogesh V. Joshi (2007), "New Product Diffusion with Influentials and Imitators," *Marketing Science*, 26 (3), 400–421.
- and Stefan Wuyts (2007), *Social Networks and Marketing*. Cambridge, MA: Marketing Science Institute.
- Venkatraman, Meera P. (1990), "Opinion Leadership, Enduring Involvement and Characteristics of Opinion Leaders: A Moderating or Mediating Relationship?" working paper, School of Management, Boston University.

Watts, J. Duncan and Peter Sheridan Dodds (2007), "Influentials, Networks, and Public Opinion Formation," *Journal of Consumer Research*, 34 (4), 441–58.

Weimann, Gabriel (1991), "The Influentials: Back to the Concept of Opinion Leaders?" *Public Opinion Quarterly*, 55 (2), 267–79.

——— (1994), *The Influentials: People Who Influence People*. Albany: State University of New York Press.

Yang, Sha, Vishal Narayan, and Henry Assael (2006), "Estimating the Interdependence of Television Program Viewership Between Spouses: A Bayesian Simulations Equation Model," *Marketing Science*, 25 (4), 336–49.



Survey Michigan

Courses in Survey Research Techniques

June 1 – July 24, 2009

www.isr.umich.edu/src/si



62nd annual **Summer Institute** in Survey Research Techniques
Survey Research Center, Institute for Social Research, University of Michigan
For more information: Phone (734) 764-6595, Toll-Free (877) 880-9389