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In word-of-mouth seeding programs, customer word of mouth can generate value through market expansion; in other words, it can gain customers who would not otherwise have bought the product. Alternatively, word of mouth can generate value by accelerating the purchases of customers who would have purchased anyway. This article presents the first investigation exploring how acceleration and expansion combine to generate value in a word-of-mouth seeding program for a new product. The authors define a program's "social value" as the global change, over the entire social system, in customer equity that can be attributed to the word-of-mouth program participants. They compute programs' social value in various scenarios using an agent-based simulation model and empirical connectivity data on 12 social networks in various markets as input to the simulation. The authors show how expansion and acceleration integrate to create programs' social value and illustrate how the role of each is affected by factors such as competition, program targeting, profit decline, and retention. These results have substantial implications for the design and evaluation of word-of-mouth marketing programs and of the profit impact of word of mouth in general.

Keywords: word of mouth, customer equity, new product diffusion, seeding, agent-based models, social networks

Decomposing the Value of Word-of-Mouth Seeding Programs: Acceleration Versus Expansion

Consider the following word-of-mouth seeding marketing campaigns:

- In 2006, Philips gave away power toothbrushes (Sonicare Essence) to 33,000 North Americans. Each recipient also received five $10 rebates to give to others. Philips estimated the campaign to have reached approximately 1.5 million potential customers (Rosen 2009).
- In 2008, Hewlett-Packard (HP) gave 31 prominent bloggers the new HP Dragon laptop computer to create online contests for which the Dragon was the prize. As a result, HP observed an immediate 85% bump in Dragon sales and a 15% increase in traffic to its website (Quinton 2008).
- In 2009, Microsoft hosted thousands of parties in 14 countries to help introduce the Windows 7 operating system. Microsoft estimated that the information disseminated in those parties may have eventually reached seven million people (McMains 2010).
- In 2009, Ford gave a Ford Fiesta to 100 bloggers so they could help promote the new model. The purpose of this program was "to get the model's target audience to drive, and hopefully chatter about the car" (Tegler 2009).

Industry leaders agree that a key obstacle for widespread adoption of such seeding programs is the lack of ability to

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measure their financial performance accurately (Wasserman 2008). As an industry observer noted, "Building a word-of-mouth campaign is in many ways the easy part; measuring its effectiveness is a different matter entirely" (Miles 2006). Such a challenge coincides with appeals to marketers to improve their understanding of the social aspects of customer profitability (Gupta et al. 2006; Rust and Chung 2006). While there is initial evidence regarding seeding programs' financial contributions (Godes and Mayzlin 2009; Kumar, Petersen, and Leone 2010; Schmitt, Skiera, and Van den Bulte 2011; Toubia, Stephen, and Freud 2009), there is still a need to better understand how to generate these programs' monetary value.

The literature presents two main approaches for the measurement of word-of-mouth value. One approach focuses on how many new people are affected and disregards the question of the point in time at which they are influenced (Hinz et al. 2011; Watts and Dodds 2007). The second approach assumes that the profit results from the eventual adopters' acceleration of adoption (Ho et al. 2012; Hogan, Lemon, and Libai 2003; Jain, Mahajan, and Muller 1995). Yet as we show here, the value of seeding programs (particularly in competitive markets) derives from the interaction of *both* mechanisms: through market expansion, in which the firm acquires a customer who otherwise would not have purchased the brand, and through customer acceleration, in which additional revenues stem from accelerated purchases of customers who would have purchased the brand in any case, but at a later time.[1]

In this article, we demonstrate how the integration of customer acceleration and market expansion is fundamental to understanding both the value created by word-of-mouth programs and customers' word of mouth in general. Thus, the acceleration/expansion dynamic is fundamental to answering questions such as the following: Why will a stronger brand benefit less from a word-of-mouth program? How will a future decline in price or a lower retention rate affect the benefit from the program? How will targeting influential customers change a program's value? How can a shorter measurement horizon lead to a considerable overestimation of the benefit of a word-of-mouth program? Given the increasing role of word-of-mouth programs in marketing-mix activities, this issue is therefore of essential managerial importance.

To investigate these dynamics, we first define a customer social value metric that measures the influence of a group of customers' communication on brand-related customer equity over the entire social system. We then use agent-based modeling, a simulation method researchers have increasingly used in recent years to untangle complex marketing problems (Goldenberg, Libai, and Muller 2001; Rand and Rust 2011), to show how customer social value is generated under various types of market conditions. We use real-life connectivity data on 12 social network structures and the agent-based model to examine a common situation that is consistent with the examples presented at the beginning of this article: a new product is introduced into a competitive market through a "seeding program" in which an initial group of people (the "seed") receives the product early on so their word of mouth can begin to drive diffusion (Lehmann and Esteban-Bravo 2006; Libai, Muller, and Peres 2005). The seeding program's social value consists of any surplus generated through the program that the company would not have achieved in its absence. We measure the seed's social value in various market scenarios and analyze how market expansion, customer acceleration, or both typically drive this social value. Among our main results are the following:

- For similar brands, market expansion dominates seeding programs' value. When two similar brands enter the market and one of them launches a seeding program, we find that market expansion, rather than acceleration, generates the majority of the long-term social value the word-of-mouth program creates.
- Stronger brands accelerate more, yet profit less, from a program. For dissimilar brands, the stronger the brand that operates the program, the lower the program's social value, and the larger the share of social value resulting from acceleration.
- Acceleration primarily drives seeding programs aimed at influential customers. Influential programs, in which the seeding program targets the most connected or the most persuasive people, generate more social value on average than programs targeted at random people. Relative to random programs, acceleration drives a larger share of influential programs' social value.
- Lower customer retention rate is associated with a smaller role of acceleration. In the presence of customer attrition (after the product's adoption), a lower retention rate (i.e., higher disadoption rate) is associated with a reduced role of acceleration in relation to expansion.
- Temporal profit decline is associated with a larger role of acceleration. When profits per customer decline over the product's life cycle (as often happens due to price decline), acceleration's importance increases at the expense of market expansion.
- Short-term planning creates overestimation bias. When a firm measures the seeding program's social value in the short run, it may overestimate the program's contribution. This is due to the misinterpretation of acceleration as expansion. Given that firms tend to use short-term effects to make conclusions about such programs' contributions, this issue is of essential importance to the valuation of the measurement of word-of-mouth programs' return on investment for a new product.

ON SEEDING AND EXPANSION VERSUS ACCELERATION

Although marketers widely accept word of mouth as an important profit driver, documenting its effect on profitability is not straightforward, because the way social interactions combine to generate market-level effects is complex (Godes et al. 2005). Recently, however, marketing researchers have gained access to better data and methods, enabling a closer examination of word of mouth's effectiveness. For example, research has shown word of mouth to affect television ratings (Godes and Mayzlin 2004), movie sales (Liu 2006), book sales (Chevalier and Mayzlin 2006), stock prices (Luo 2009), customer acquisition through online networking sites (Trusov, Bucklin, and Pauwels 2009), and new customer profitability (Villanueva, Yoo, and Hanssens 2008). Mar-

[1]Market researchers use an analogous decomposition for supermarket products in which the aim is to decompose the products' sales promotion "bump" into the following components: the switch from another brand, additional consumption, and the acceleration of future consumption (Van Heerde and Neslin 2008). While the two types of marketing-mix actions—namely, promotions and seeding—differ considerably in the basic processes that drive the value creation and the availability of data, they share the decomposition of expansion and acceleration as the main drivers of the marketing tool's value.

keters are consequently better able to understand the drivers of various word-of-mouth programs' success, such as word-of-mouth agent programs (Godes and Mayzlin 2009), viral marketing (Hinz et al. 2011; Van der Lans et al. 2010), and referral rewards programs (Kornish and Li 2010; Schmitt, Skiera, and Van den Bulte 2011).

Yet, the literature stream has thus far overlooked the distinction between two main underlying mechanisms through which word-of-mouth communications generate value to the firm: market expansion and customer acceleration. "Market expansion" refers to the contribution of a customer, who, absent word of mouth, would not have adopted the product or would have adopted a competing brand. Industry practice has generally focused on market expansion, specifically, first-degree expansion. A customer's word-of-mouth contribution is measured as the sum of the profits obtained from all new customers that this person directly helped acquire (Nowinski 2008). However, we can take higher degrees of separation into account (Hogan, Lemon, and Libai 2004). Kumar, Petersen, and Leone (2010) suggest distinguishing two types of customers: those who would not have purchased without word of mouth and those who would. For the former, their full lifetime value of purchases is added to the lifetime value of the referring customer. For the latter, only the savings in customer acquisition costs are added.

"Customer acceleration" refers to the contribution of a customer who, absent word of mouth, would have adopted the new brand, but at a later date. This is consistent with marketing's prominence as an accelerator of cash streams (Srivastava, Shervani, and Fahey 1998). In the context of a new product's category-level diffusion, Hogan, Lemon, and Libai (2003) show that a customer's word-of-mouth value stems from his or her having helped accelerate growth, and Jain, Mahajan, and Muller (1995) and Ho et al. (2012) demonstrate how new product samples and seeding accelerate growth and increase profitability.

SEEDING PROGRAMS

We focus on the role of acceleration and expansion in the context of seeding programs. Marketers typically use seeding programs to help spread information about a new product or idea by getting a group of target customers to adopt the product early on in an effort to enhance the contagion process for other customers (Lehmann and Estaban-Bravo 2006). Hinz et al. (2011) identify four critical factors for a successful seeding program: content (e.g., Berger and Schwartz 2011), network structure (e.g., Stephen, Dover, and Goldenberg 2010), behavioral incentives (e.g., Libai et al. 2010), and the seeding strategy itself—specifically, the process of choosing the seeded people.

Researchers have drawn much attention to the issue of optimal seeding. Although some research has focused on the spatial aspects of seeding (i.e., studying which markets [Libai, Muller, and Peres 2005] or which channels [Choi, Hui, and Bell 2010] are optimal for seeding), much research has examined an issue surrounding the profiles of the seeded people. The literature on customer-to-customer interactions has devoted much attention to the role of people who have a disproportional effect on others (often labeled "opinion leaders," "influentials," or "influencers") (Iyengar, Van den Bulte, and Valente 2011; Katona, Zubcsek, and Sarvary 2011; Nair, Manchanda, and Bhatia 2010; Trusov, Bodapati, and Bucklin 2010). Naturally, such people are candidates to be targets of seeding efforts.

Previous research has focused on three types of people who are candidates for seeding targets. The first type (and probably the most referred to in this sense) is the "hubs," or those most connected to others (Goldenberg et al. 2009; Watts and Dodds 2007). The assumption is that greater connectivity will lead to a greater number of others influenced. The second target type is the "persuaders" or "experts," those whose disproportional effect is not measured in audience size but in the persuasiveness of each interaction. This effect can stem from their peers holding them in high esteem (Keller and Berry 2003) or because they are experts on a subject, either from previous knowledge or because they are heavy users (Iyengar, Van den Bulte, and Valente 2011). The third type is those who experience an advantage due to a network position that enhances their influence in the social system. Measures of such a position can include betweenness to indicate a bridge between various subnetworks (Hinz et al. 2011) or a clustering coefficient that indicates little overlap between neighbors (Stonedahl, Rand, and Wilensky 2010).

There is no clear answer to which type is a better target for seeding purposes. Computer science research suggests that determining the optimal number and identity of the people who will form the seed is computationally complex, and therefore there are efforts to identify efficient algorithms toward this end (e.g., Kempe, Kleinberg, and Tardos 2003, 2005). Hubs are probably the most used target, largely because they are the easiest to identify given some information on connectivity. Watts and Dodds (2007) argue that hubs do not necessarily create large cascades of influence as people might expect. Yet considerable analytical (Zubscek and Sarvary 2011) and empirical (Hinz et al. 2011) work has proved the advantage of targeting hubs. In addition, it is unclear whether targeting a "pure" type is the best strategy. Stonedahl, Rand, and Wilensky (2010), for example, show that although targeting hubs is a good approach for classical network structures, in a real-world Twitter network, combining high degree with a network position (i.e., high clustering) yields better results.

Our focus is not to identify the best targeting type but rather to understand the process that leads the seeding program to create profitability. We highlight several issues in this regard. First, from the firm's perspective, customer equity or the net present value (NPV) of current and future customer profits should be the measure of success of any marketing initiative (Rust, Lemon, and Zeithaml 2004), which is also the case for word-of-mouth-related impact (Goldenberg et al. 2007; Stonedahl, Rand, and Wilensky 2010). Second, market researchers have typically assessed the success of seeding programs from either the final number of people who adopted or showed awareness (Hinz et al. 2011; Watts and Dodds 2007) or the effect of acceleration on the NPV (Jain, Mahajan, and Muller 1995) but not on the combined effect of both. This issue is notable, given that researchers have generally investigated the effect of the seeding programs on a single firm or product rather than products in a competitive environment. In a competitive environment, both acceleration and expansion combine to create profitability. If an adopter of a certain brand affects someone who would have purchased this brand anyway, it is a case of acceleration. If they would have otherwise purchased a competing brand, it is a case of expansion. Untangling the dynamics of the two is thus essential in understanding seeding programs' profitability.

In this article, we first define the concept of the social value of a group of customers. Second, we present the agent-based model setting, in which we examine seeding programs as well as network structure data as input to the simulations. We then explore the fundamental roles of acceleration and expansion in social value and how they change under various market scenarios and in an example of managerial misclassification. We conclude with a discussion and description of limitations.

THE SOCIAL VALUE OF A WORD-OF-MOUTH SEEDING PROGRAM

As a preliminary step in decomposing word-of-mouth value into market expansion and acceleration, we must define and measure an individual's word-of-mouth contribution. In the classic 1946 film *It's a Wonderful Life*, an angel helps a businessman on the verge of suicide by showing him what life in his town would have been like had he never existed. The message is that only in someone's absence can we truly appreciate his or her value. We suggest an analogous premise for assessing the customers' social value: Assume that a customer in a social system purchases a brand but does not generate word of mouth about it. The brand will eventually spread in the system due to advertising and word of mouth from other customers, and the firm will ultimately have a certain level of overall profits. This constitutes a scenario of "life without that customer's word of mouth."

Next, consider an identical scenario, with the exception that this person does generate word of mouth about the brand. This local change causes a shock to the social system and therefore has implications for the information flow through the entire system. As a result of that customer's influence, some people may purchase the product at a different time, and some who would not otherwise have purchased the product may adopt it. These effects will translate into a change in profits due to both acceleration and market expansion. The only difference between the two scenarios is the presence of word of mouth generated by an individual customer; thus, we define the difference in profits between the two scenarios as this person's social value.

Note that researchers have used several terms to measure of the worth of a customer's social effect. These include "referral value," for value generated through referral programs; "influencer value," for nonincentivized word of mouth (Kumar, Petersen, and Leone 2010); "indirect value" (Hogan, Lemon, and Libai 2003); "influence value" (Ho et al. 2012); and "word-of-mouth value" (Wangenheim and Bayón 2007). Although we recognize that the term "social" might create confusion with society-related issues such as social responsibility, we prefer the term "social value" because it potentially includes a wider range of effects than those confined to word of mouth (e.g., observational learning, peer pressure). It is also more specific than broader terms such as "indirect effects," which may include non-social effects (e.g., helping the firm to learn).

To calculate the social value of a seeding group, market researchers should assess, at the social-system level, the monetary results achieved when the seeding group adopts and spreads word of mouth about a product early on. They should then compare the results with those achieved in the absence of the seeding program, in which the group members adopt the product like any other member of the social system. Beginning with the social value of customers in general and using formal notations, we consider a social system of size N that begins to adopt a new product. Each adoption brings the firm a value at the time of adoption. We can assume either a durable product with a one-time purchase or a repeat-purchase product whose value is the estimated lifetime value. Observing the profitability generated by a group of g customers out of the overall N customers, we consider the following types of profitability: the direct value $V_{direct}(g)$, which is the total dollar value the g customers' purchases generate, and the social value $V_{social}(g)$, which is the total dollar value the g customers' effect generates on the other (N – g) customers. Total value $V_{total}(g)$ is the sum of both: $V_{total}(g) = V_{direct}(g) + V_{social}(g)$.

Now this group of g customers is exposed to a program under which group members adopt the product at launch rather than at later times. The added value of the program, denoted by ΔV^*_{total}, is the difference in customer equity—in other words, the difference in total value for the entire social system (N) between the scenario with the program and the scenario without the program, or $\Delta V^*_{total}(g) = V^*_{total}(N) - V_{total}(N)$. The program value stems from the two following sources:

- Direct value: the g customers' early adoption generates value due to the time value of money. If initially the g customers' direct value was $V_{direct}(g)$, it is now the sum of their purchases at time zero, denoted by $V^*_{direct}(g)$. Therefore, the program's marginal direct value is $\Delta V^*_{direct}(g) = V^*_{direct}(g) - V_{direct}(g)$.
- Social value: the program's marginal social value considers the g customers' influence on others. It follows that the program's social value is its total value minus its direct value, and therefore Equation 1 presents the social value of a program:

$$\Delta V^*_{social}(g) = \Delta V^*_{total}(g) - \Delta V^*_{direct}(g) = V^*_{total}(N) - V_{total}(N) - [V^*_{direct}(g) - V_{direct}(g)]. \tag{1}$$

AN AGENT-BASED MODEL OF A SEEDING PROGRAM

Finding the social value of a seeding program requires the comparison of the brand's customer equity in two would-be worlds: one with the program and the other without. To do so, we used stochastic cellular automata, an agent-based modeling technique that simulates aggregate consequences on the basis of local interactions among individual members of a population (Goldenberg, Libai, and Muller 2001). As Rand and Rust (2011) note regarding new products, the patterns of growth in the market that result from the interaction of many consumers might be much more complex than the consumers' individual adoption rules. The advantage of the agent-based approach is that researchers perform modeling at the individual level, which does not require knowledge of or assumptions about the macrodynamics. As a result, marketing studies are increasingly using agent-based models, particularly when analyzing new product growth (Delre et al. 2010; Garber et al. 2004; Garcia 2005; Shaikh, Rangaswamy, and Balakrishnan 2006).

Given the increased use of agent-based models in marketing, Rand and Rust (2011) have recently introduced detailed guidelines on how to use and validate them in this context. In Web Appendix A (www.marketingpower.com/jmr_webappendix), we present more details on the basic approach of our agent-based model and elaborate on its consistency with Rand and Rust's (2011) suggested two main criteria of verification and validation. In the following subsections, we present the essence of our approach on two fundamental aspects of the agent-based model: the structure of the social network and the adoption dynamics of the participants.

Social Network Structure

Given the increasing accessibility of social network data, a promising yet still underused approach is to use real-life network data to design the social structure that forms the foundation of the agent-based model, possibly using multiple networks if the aim is to generalize beyond the single-network case. We examine the social value of seeding programs using empirical connectivity data on the 12 networks presented in Table 1 and Figure 1. With the exception of the last two networks, all the networks we examine are exact replicas of actual network nodes and ties. Note that we use these networks only as examples of real-life connectivity structures and do not relate to any of their other aspects. Next, we provide a short description of the networks (more details are available in Web Appendix B at www.marketingpower.com/jmr_webappendix).

Several researchers have published articles about three of the social networks (Networks 1–3), and these authors have graciously shared their data with us. These networks include an e-mail network at Rovira i Virgili University (URV) in Tarragona, Spain (Guimera et al. 2003); the main component of the network of users of the Pretty Good Privacy (PGP) algorithm for secure information exchange (Boguña, Pastor-Satorras, and Diaz-Guilera 2004); and the social network of Cameroonian women in the village of Mewocuda (Valente et al. 1997). We collected data on six additional networks (Networks 4–9) specifically for this study in collaboration with Lithium Technologies, a leading provider of social customer relationship management solutions that power enterprise customer networks for major U.S. and global brands. We obtained these six networks from online communities of major national brands in four industries: technology, entertainment, retail, and services. In these online communities, members talk about product markets and brands and discuss issues such as ideas for new products and solutions to brand-related problems. We obtained data on Network 10 from YouTube; though it is widely known as a media site, it also operates as a social network for users who upload videos. The social network we present here reflects ties among 4000 YouTube members.

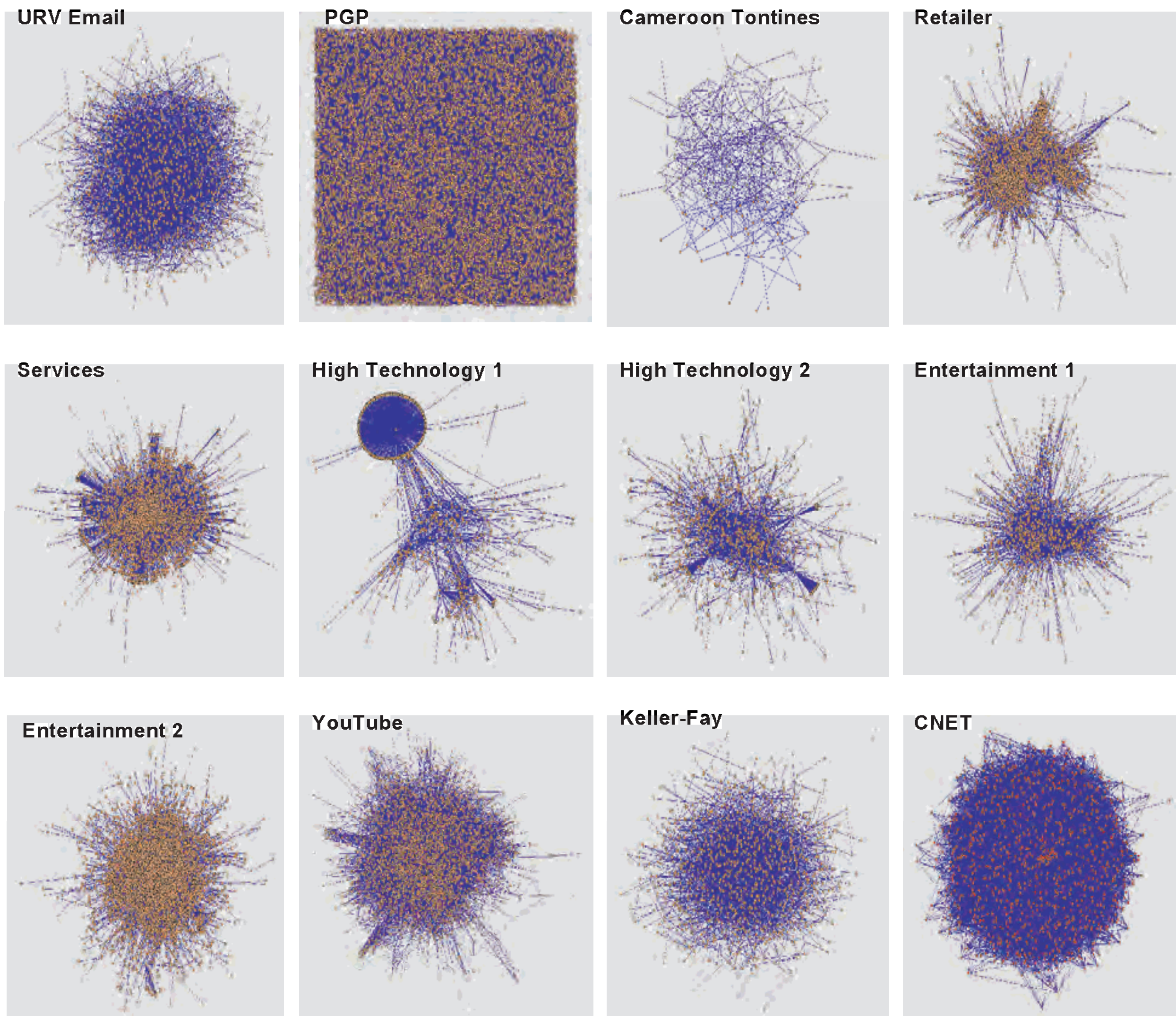
The data for Networks 1–10 fully mirror the relations among members (i.e., they constitute exact replicas of actual network nodes and ties). In Networks 11 and 12, we did not have access to the actual network connections but rather only to the degree distributions (i.e., the distribution of the number of connections throughout the population). Therefore, for each of these networks, we constructed a randomly assigned social network of 1000 units on the basis of a reported degree distribution. Network 11 uses a distribution based on the Keller-Fay group's TalkTrack (Keller 2007), an award-winning ongoing survey of American consumers ages 13–69 that reports on word-of-mouth activity as well as social network size. Network 12 uses the degree distribution based on the reported average number of ties of more than 11,000 customers who visited the CNET site and responded to a survey on social networks (Smith et al. 2007).

Table 1 presents the key network parameters typically used to characterize networks in social network literature (e.g., Newman 2003; Van den Bulte and Wuyts 2007).

Table 1
NETWORK CHARACTERISTICS

	Network	*Description*	*Reference*	*Size*	*Average Degree*	*Average Degree Top 10%*	*Average Separation*	*Clustering Coefficient*
Published Networks								
1	URV e-mail network	University e-mail network	Guimera et al. (2003)	1133	9.6	31.3	3.6	.220
2	PGP	Software user network	Boguña et al. (2004)	10,680	4.6	22.5	7.5	.266
3	Cameroon Tontines	Cameroonian women	Valente et al. (1997)	161	6.0	13.9	3.2	.128
Networks Collected for This Study								
4	Retailer	Lithium network		4968	8.8	60.0	3.5	.502
5	Services	Lithium network		4457	13.5	98.6	2.8	.481
6	High-tech 1	Lithium network		3574	2.6	16.4	2.8	.145
7	High-tech 2	Lithium network		3663	2.6	15.8	3.4	.176
8	Entertainment 1	Lithium network		1496	5.3	33.5	3.5	.285
9	Entertainment 2	Lithium network		7045	4.2	28.4	3.6	.239
10	YouTube	Networking site		4160	8.5	30.2	4.0	.073
Empirical-Degree Random Networks								
11	Keller-Fay	TalkTrack word-of-mouth survey	Keller (2007)	1000	6.0	17.7	5.0	.056
12	CNET	Survey on social networks	Smith et al. (2007)	1000	42.2	106.9	2.2	.110
	Average			3611	9.5	39.6	3.8	.22

Figure 1
NETWORK GRAPHS



These parameters include the "size" of the network (i.e., number of nodes); the "average degree," or number of members in direct contact, both for the entire population and for the 10% of members with the most connections; the "average separation," or the average distance of each member from the rest of the network; and the average "clustering coefficient," which represents the tendency to form clustered groups of connected individuals (CC1 in Newman 2003). Table 1 and Figure 1 demonstrate the diversity of the networks on which we perform the simulations. Note that all the networks we present have a single major component: they are nearly free of isolated units or isolated clusters. Although this type of network is the most commonly described in the literature, other network structures can lead to differing diffusion dynamics.

Adoption Dynamics

For each network, we began with a social system of non-adopters in a discrete time frame. In each period, two brands (A and B) compete for the potential adopters. Each cell can accept one of three states: "0," "A," or "B," respectively denoting a potential customer who has not adopted the innovative product, one who has adopted Brand A, or one who has adopted Brand B. In accordance with classical diffusion modeling, the transition from potential adopter to actual adopter depends on two factors: (1) external influence, represented by the probability δ that a person will be influenced by salespeople, advertising, promotions, and other marketing efforts, and will consequently adopt the brand, and (2) internal influence, represented by the probability q that during a given time period, a person will be affected by an interaction (e.g., word of mouth, imitation) with another member of the same social network who has already adopted the brand.

To take into account the possible heterogeneous nature of customer propensity to be affected by others, we assume that the value of q is normally distributed throughout the network. For robustness, we also examined cases in which q is distributed in a power-law distribution with the power-law exponent parameter simulated in the commonly used range of 2–3. We also observed a uniform distribution in which the range is plus/minus the standard deviation used in the normal distribution analysis. We found that the following results are robust to the specification of q. Note that q's heterogeneity, coupled with the range of parameter values for the advertising coefficient (δ), somewhat mitigates the probability that transmitting word of mouth is endogenous to the marketing-mix variables (Stephen and Galak 2012). Yet here, we assume independence as per classical diffusion theory.

In building innovation adoption models at the category level (e.g., Goldenberg, Libai, and Muller 2001), previous research has operationalized the status shift of an individual i at time t from nonadopter to adopter as a cascade of influences in which each adopter connected to i can independently try to convince i to adopt. Thus, the adoption probability of i is 1 minus the probability that all these adopters, as well as the advertising efforts, failed the task: $p_i(t) = 1 - (1 - \delta)(1 - q_i)^{N_i(t)}$, where $N_i(t)$ is the number of adopters in i's personal social network.

We now extend this model to describe adoption in a competitive scenario. Our basic assumption is that the category-level adoption decision can be extended to the brand level. While one could argue in favor of a two-stage process in which consumers first adopt the category and then choose a brand, our approach is consistent with most of the diffusion literature, specifically with brand-level models that have demonstrated a good fit to empirical data (Libai, Muller, and Peres 2009a, b). Assume two brands, A and B, each having its own external influence δ_A and δ_B and internal influence q_{iA} and q_{iB} for each person in the network. Adopters of A and B independently influence a potential adopter i to consider their respective brands. The probability of at least one adopter of A or B successfully influencing i to consider brand A or B is as follows:

$$p_i^A(t) = 1 - (1 - \delta_A)(1 - q_{iA})^{N_i^A(t)}, \text{ and} \tag{2}$$

$$p_i^B(t) = 1 - (1 - \delta_B)(1 - q_{iB})^{N_i^B(t)}, \tag{3}$$

where N_i^A and N_i^B denote all consumers in i's personal social network who have adopted either A or B. The probability of i being successfully influenced regarding Brand A but not Brand B is $p_i^A(1 - p_i^B)$. Having thus been influenced by A but by B results in adoption of Brand A. The probability of i being informed about both products is $p_i^A p_i^B$, and in this case, consumer i will adopt in accordance with the ratio of probabilities α. Therefore, the probabilities of i adopting A, B, or neither are given, respectively, by the following:

$$p_i(\text{adopt A}) = p_i^A\left(1 - p_i^B\right) + \alpha_A p_i^A p_i^B,$$

$$p_i(\text{adopt B}) = p_i^B\left(1 - p_i^A\right) + \alpha_B p_i^A p_i^B,$$

$$p_i(\text{adopt none}) = \left(1 - p_i^B\right)\left(1 - p_i^A\right), \text{ where}$$

$$\alpha_A = \frac{p_i^A}{p_i^A + p_i^B}, \alpha_B = 1 - \alpha_A.$$

In the simulation, we performed the adoption probability's realization by drawing, for each unit in each period, a random number from a uniform distribution and comparing it to adoption probabilities p_i^A and p_i^B. The parameters δ, q, and the number of periods vary between simulations, and we chose their ranges to be consistent with previous research regarding δ's and q's ranges in diffusion and agent-based models (e.g., Goldenberg et al. 2007). Table C1 in Web Appendix C (www.marketingpower.com/jmr_webappendix) summarizes the parameter ranges. The simulation ends after 30 time periods, which is consistent with common practice in similar models (e.g., Goldenberg, Libai, and Muller 2010). Given our parameter values, the 30 time periods assume that most of the market has adopted by that point and thus the market potential is in most cases fully tapped. Moreover, given the discount factor, any additional profitability beyond 30 periods is negligible. Last, we programmed the simulations in C++; the pseudocode is available in Web Appendix D (www.marketingpower.com/jmr_webappendix).

The Seeding Program and Measurement of Social Value

We used a seeding program in which a selected group of people initiates the diffusion process in the network. We varied two key characteristics for the seeding program: number of members and types of members. Following discussions with managers and reports on industry practice (e.g., Rosen 2009), we varied the program size from .5% to 5% of the potential market. Our second concern was choosing whom to target as program members. As we discussed previously, although the firm might seed randomly, it can also target two types of influential customers: those who have a large number of connections (hubs) and those who exert inordinate influence over others (experts). Therefore, we consider three groups:

- Random seeding: we formed a group of randomly selected customers who would adopt the brand at time 0.
- Influential seeding (hubs): For each network, we randomly chose the seed members from the 10% of those members with the highest number of connections, that is, the people with the highest degree of influence (Watts and Dodds 2007).
- Influential seeding (experts): We randomly chose the seed members from the 10% of those members with the highest internal coefficient, that is, those who are most persuasive per contact (q).

We drew a new group of seed members for each simulation. To make a valid comparison, we used the same size seed group (in terms of the proportion of seed members to the size of the potential market) in all three seeding types. As previously explained, we define social value as the net difference in customer equity between a scenario with the program and a scenario with the exact same parameters but without the program. We measured the customer equity for a brand, which is the sum of the discounted cash flow from all adopters over all the time periods. We assumed that each adopter contributes a normalized value of one monetary unit. This value can represent a one-time purchase for a durable good or the lifetime value at the time of adoption that takes into account retention rate for a repeat-purchase product. Consistent with many of the agent-based profitability simulations, we used a discount rate of 10% per time period (e.g., Goldenberg et al. 2007). Subsequently, we examine the effects of changing the value of future cash flows.

ACCELERATION, MARKET EXPANSION, AND SOCIAL VALUE: RESULTS

For each of the 12 networks, we ran simulations of the diffusion of a new product and varied all the parameters in a full factorial design, assessing the social value we obtained. We compared four scenarios: (1) no seeding program, (2) Brand A operates a random seeding program, (3) Brand A operates an influential hubs seeding program, and (4) Brand A operates an influential experts seeding program. Because we were interested in measuring the differences in social value across scenarios, in each run, we used the same series of randomly drawn numbers to realize individual adoption probabilities. Thus, we attribute the differences to changes in the program rather than to random fluctuations. To avoid stochastic effects of a single run, we ran each combination of parameters in each network 20 times with varying realizations. For each network and scenario, we report the average results across all runs and parameter values.

We divide the results according to three broad areas. First, we examine the fundamental role of acceleration and acquisition in the social value of seeding programs using the metric of acceleration ratio as the basis for the analysis. We then turn our attention to changes in market scenarios such as differential brand strength and declining profits. Last, we report the effect of biases created by misspecification of market conditions such as considering a short time horizon and ignoring disadoption. In this section, we present the results, considering one factor at a time and one network at a time. In the following section, we demonstrate how the results hold when considering the joint effect of all factors as well as all networks.

The Fundamental Role of Acceleration and Expansion in Social Value

In this subsection, we expand on the roles of acceleration and expansion in seeding programs. Table 2 presents detailed results for the Keller-Fay network, and Table 3 summarizes the main results for the 12 networks. To better understand Table 3's results, observe the example in Table 2, column 1: if Brand A begins a random seeding program, its average equity increases from a value of approximately 225 (in the "no seeding program" scenario) to 375, a gain of approximately 67% (indicated in row 2, column 4). Following our definition of social value, this difference of 150 constitutes the social value of the group of customers who formed the seed. Columns 1–2 of Table 3 present social value (in percentage, equivalent to column 4 in Table 2) for each network.

Because our simulations have the complete data on adoption in all scenarios, we can decompose the social value into its components of market expansion and acceleration by examining the scenarios with and without a program and tracking adoption on the part of each individual unit. We define a metric labeled "acceleration ratio," or the proportion of the total customer equity gain (compared with no program) attributable to customer acceleration (columns 3 and 4 of Table 3). Notably, we can also compute the acceleration ratio from the aggregate results, as we illustrate through the Keller-Fay example in Table 2. When only Brand A operates a random program, Brand A's customer equity increases by approximately \$150 (375.5 – 225.3), whereas Brand B's customer equity decreases by \$97 (127.9 – 224.8). Because we assume only two competitors and no outside option (postulating that by the end of the time horizon, virtually the entire market will have adopted the product), it follows that A gained what B lost, and thus,

Table 2

CUSTOMER EQUITY AND NUMBER OF ADOPTERS FOR PROGRAMS TARGETING RANDOM CUSTOMERS AND INFLUENTIALS-HUBS: KELLER-FAY NETWORK

Scenario	*1 Customer Equity (\$) Brand A*	*2 Customer Equity (\$) Brand B*	*3 Total Customer Equity (\$)*	*4 Social Value Brand A*[a]
1. No seeding program	225.3	224.8	450.2	
2. Random seeding by Brand A	375.5	127.9	503.4	67%
3. Influential-hubs seeding by Brand A	447.7	92.5	540.1	99%

[a]Compared with the no seeding program option (first row).

Table 3

ADDITIONAL SOCIAL VALUE OF A BRAND OPERATING A SEEDING PROGRAM AS COMPARED WITH THE NO-PROGRAM SCENARIO

No.	*Network*	*1. Social Value Random Program*	*2. Social Value Influential Program: Hubs*	*2. Social Value Influential Program: Experts*	*3. Acceleration Ratio*[a] *Random Program*	*4. Acceleration Ratio*[a] *Influential Program: Hubs*	*4. Acceleration Ratio*[a] *Influential Program: Experts*
1	URV e-mail network	79%	109%	92%	28%	33%	31%
2	PGP	58%	82%	70%	35%	39%	39%
3	Cameroon Tontines	86%	112%	99%	33%	36%	36%
4	Retailer	92%	114%	100%	20%	27%	22%
5	Services	96%	112%	101%	18%	24%	20%
6	High-tech 1	83%	94%	89%	19%	25%	20%
7	High-tech 2	79%	103%	89%	24%	30%	26%
8	Entertainment 1	81%	112%	92%	25%	32%	27%
9	Entertainment 2	84%	104%	91%	20%	27%	22%
10	YouTube	78%	109%	92%	28%	34%	31%
11	Keller-Fay	67%	99%	82%	35%	40%	39%
12	CNET	76%	101%	83%	30%	35%	32%
	Average	80.2%	104.5%	90.6%	25.9%	31.5%	28.4%

[a]Acceleration ratio is the proportion of the total gain in customer equity attributable to acceleration.

we can conclude that 97/150 = 65% is the percentage gained through market expansion and the remaining 35% is the percentage that stems from customer acceleration. Therefore, Brand A's acceleration ratio in column 3, row 11 (Keller-Fay) of Table 4 is 35%.

In columns 3 and 4 in Table 3, note that most of the seeding program's social value derives from market expansion. On average, acceleration ratio is 26% for random targeting and 32% and 28% for influential targeting of hubs and experts, respectively. In all cases, the acceleration ratio is well below the 50% level. The results in Table 3 are consistent across various networks, even though the networks themselves vary greatly in their basic characteristics (see Table 1). The role of acceleration is also related to the program's profitability: we observe a correlation of .7 for a random program and .6 for an influential program between the percentage of market expansion and the profitability of the program, indicating that most value added is a result of market expansion.

Result 1: Consistent across network structures for equal brands and fixed discount factor, market expansion dominates the social value of word-of-mouth programs.

Influential Versus Random Programs

From Table 3, we observe that our results are generally consistent for both random and influential programs, and yet magnitude varies. It is worthwhile to better understand how acceleration and expansion affect the difference between the two cases. Table 3 presents a notable result: in the networks we analyzed, a random program could achieve, on average, 77% of the total social value generated by an influential hubs seeding program. We also found that influential experts seeding programs were more effective than random seeding but less effective than influential hubs seeding (consistent with Hinz et al. 2011).[2] Marketers can derive differing conclusions here, one of which might be that a program can gain most of its value without having to identify and affect influentials. Alternatively, if marketers are able to reach influentials (hubs), the social value can increase by an additional 30% over a random seeding program.

Does the seeding target affect the roles of acceleration and expansion? The last two columns of Table 3 illustrate that the customer acceleration ratio is higher for influential programs of both types than for random seeding programs. Given that influential programs generate more customer equity to begin with, the difference is even more substantial. The social value that acceleration generates in influential programs is, on average, more than 70% higher than the social value it generates in random programs. Thus, because random programs excel at acquiring customers from the competition, the influencers' extra connectivity has limited additional effect in that sense. However, influencers can more effectively enhance the acceleration of future customers.

[2]This is the one area in which the shape of the q's distribution matters. Although we found the order of efficiency (influential hubs, influential experts, and random) under both the normal and uniform distributions, in the power–law distribution, influential experts seeding was more effective than influential-hubs.

Table 4

REGRESSION RESULTS: INFLUENTIAL-HUBS PROGRAM

Independent Variable	*Coefficients*	*Standard Error*
Network size	–.00002	.0000005
Average degree	–.0048	.00013
Clustering coefficient	–.561	.0101
Discount rate	.0165	.0027
Number of periods	–.089	.0027
Seeding size	–3.457	.078
Attrition rate	–.127	.0027
Relative strength of focal brand	.236	.00269
Adjusted R-square	71.7%	

Notes: Dependent variable is acceleration ratio. All coefficients are significant at the 1% level.

Result 2: Relative to random programs, acceleration drives a greater proportion of influential programs' social value.

Other Scenarios: Differential Brand Strength and Declining Profits

In this subsection, we turn our attention to two changes in inputs that can characterize common scenarios in the market. The first is a case in which the brands differ in their strength and the second is one in which per-customer profits decline with time.

Differing brand strength. Whereas our previous analysis focused on the competition between two similar brands, we now discuss the issue of the effect of brand strength on expansion and acceleration. We ran an additional simulation, this time with Brand A's δ and q values greater than those of Brand B. The difference in brand strength is operationalized by a parameter k that multiplies the communication parameters q and δ and therefore represents the brand's relative strength. If $k = 2$, for example, it means that Brand A's δ and q values are twice those of Brand B, and therefore, Brand A is twice as strong in terms of adoption. Thus, $k = 1$ represents the equal strength case, in which most of the program's value derives from expansion, and high values of k represent cases in which Brand A resembles a monopoly. Figure 2, Panel A, illustrates the results for the Entertainment 1 Lithium network and an influential experts seeding program.

The stronger Brand A is (in terms of δ and q) relative to Brand B, the lower the social value and the higher the acceleration value of Brand A's seeding program. For example, the stronger Brand A is relative to B, the closer Brand A is to a monopoly and the less its need for a seeding program to cope with competition; thus, the role of such a program becomes more limited to accelerating adoption. In this case, when Brand A is 50% stronger, most of its value already derives from acceleration, not expansion. We obtained similar results for an influential seeding program and for the other networks (see the panel regression in the next section).

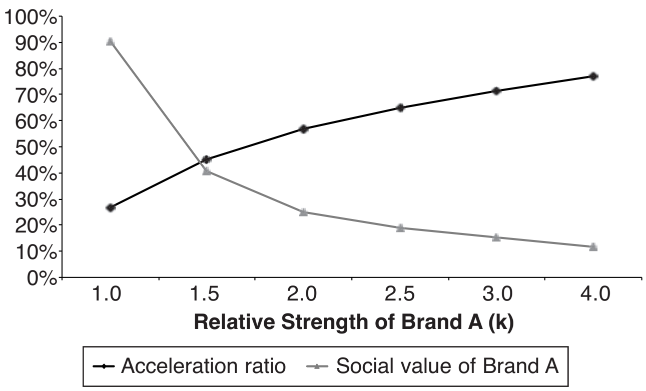
Result 3: The stronger a brand is relative to its competitor, the more acceleration drives its seeding program's social value, and the lower the program's social value is overall.

Declining profits. In the previous analysis, we assumed that future customers generate the same lifetime value as do current ones, with the only difference stemming from the

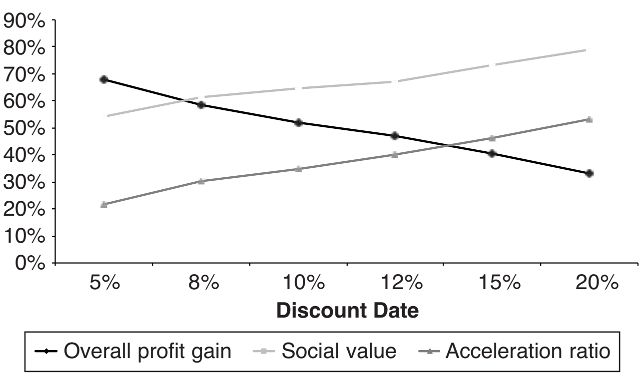
Figure 2

EFFECT OF BRAND STRENGTH AND PROFIT DECLINE ON ACCELERATION RATIO

A: Customer Acceleration Ratio and Social Value with Varying Relative Brand Strength for a Brand Operating an Influential-Experts Seeding Program; Entertainment 1 Lithium Network



B: The Effect of Decline in Profit Per Customer on Acceleration Ratio and Profitability[a]



[a]The results describe the relative profitability compared with a 0% discount rate. The results show the effect profit decline on social value gain and on acceleration ratio for a brand operating a random seeding program; Keller-Fay network.

discount factor. However, as noted in the product life cycle literature, price, and consequently per-customer profitability, often decline over the product life cycle (Golder and Tellis 2004). A compelling question is to what extent this phenomenon might change the dynamics we have reported thus far. Although price is not an explicit part of our model, we can still examine the issue by manipulating the discount rate. The discount rate is used to calculate money's present value for the firm. However, if prices (and thus profits per customer) decrease over time, future customers therefore have a lower future monetary value, which is similar to the effect of a higher discount rate.

Figure 2, Panel B, presents the effects of declining profits per customer on the results of a random seeding program for Brand A in the Keller-Fay network. In addition to considering a discount rate of 10% per period as in the analysis described previously, we considered discount rates of 5%, 8%, 12%, 15%, and 20%. The figure displays three curves: The first is Brand A's overall profit gain, achieved by implementing a random seeding program, compared with the social value with zero discount. The second curve is the social value gain as compared with the no-program case. The third curve is the acceleration ratio. (The results for the influential seeding programs, not shown in the figure, are similar in nature.)

As expected, Brand A's overall profit gains decrease with the increase in the discount rate. The acceleration ratio as well as the social value increase with a higher discount rate. This illustrates the importance of seeding programs' temporal dimension. On one extreme, when the discount rate is zero, the firm cares only about acquiring customers, regardless of when they are acquired; accelerating a customer is simply not worthwhile. On the other extreme, with a discount rate of 20%, consider the following example: suppose a customer buys the product in period 10 for \$100. It is straightforward to compute the current value (with 20% discount rate) at approximately \$16. The same purchase at period 4 is worth approximately \$48 today; thus, accelerating this customer purchase six periods ahead results in a net gain of approximately \$32. With such a high discount rate, expansion is worth approximately half of acceleration for this specific consumer. Note that this is just the monetary benefit and does not include the extra benefit from earlier word-of-mouth activity of the accelerated purchase. Thus, the lower future customers' value is (because of either falling prices or a high discount factor), the greater the effect of acceleration. The social value of a seeding program also increases because it encourages early adoption. We summarize this result as follows:

Result 4: The lower the future value of customers (as indicated by a higher discount rate or a declining price), the higher the acceleration ratio and the higher the relative social value of a program.

Potential Misspecifications

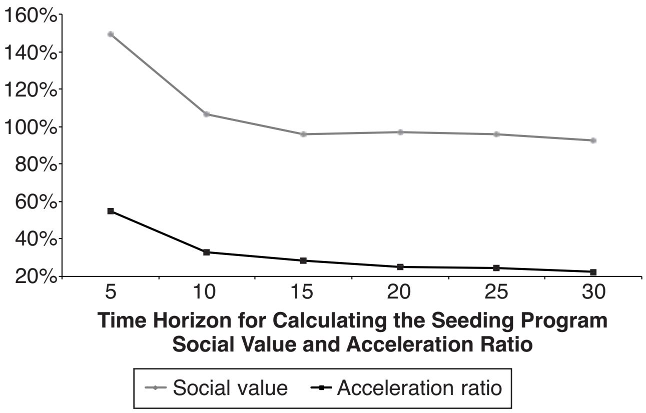
The bias of a short time horizon. In the analysis of Tables 3 and 4, we focused on the long-term horizon when we calculated the social value. However, managers may not have a long-term orientation (Verhoef and Leeflang 2009) and might consider a short-term valuation period for the seeding program to repay itself. In such a case, they will compare the program's effect several periods after launch with its expected effect without a program. Would such action change the results we previously saw, and can the expansion/acceleration dynamics help us to explain the result? To explore this issue, we reran the model for the 12 networks, this time stopping the simulation at certain points along the way and examining the results. Next, we present the results for the Keller-Fay network (for the results for the rest of the networks, see Table C2 of Web Appendix C at www.marketingpower.com/jmr_webappendix).

Figure 3, Panel A, shows how the social value and acceleration ratio of a brand operating an influential-hubs seeding program on High-tech 1 Lithium changes when we use various time horizons. The final long-term ratio is reached after 30 periods. We observe that early on, Brand A considerably overestimates the program's contribution. A manager checking the program's social value after 5 periods will measure its value as 120% compared with the no-program case. However, measuring at advanced periods shows that the social value gain is only 65%, which is the actual long-

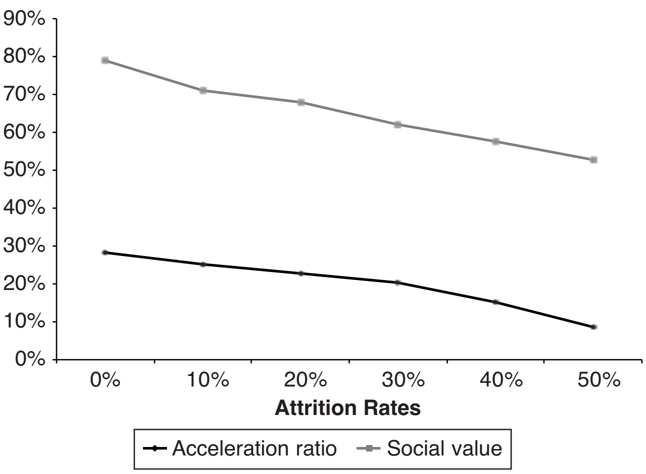
Figure 3

EFFECT OF TIME HORIZON AND RETENTION RATE ON ACCELERATION RATIO

A: The Social Value Gain and Acceleration Ratio When Various Time Horizons Are Used for a Brand Operating an Influential Hubs Seeding Program; High-Tech 1 Lithium Network



B. The Social Value Gain and Acceleration Ratio When Various Attrition Rates Are Used for a Brand Operating a Random Seeding Program; URV E-Mail Network



term gain. That is, measuring the program's value after 5 periods would lead to a considerable overestimation because when comparing the scenarios with and without the program, many consumers who adopted at the short time interval are counted as expansion as a result of the program, when they would have eventually adopted the brand at a later period and the program only helped to accelerate their adoption (if at all). That is, the underestimation of the acceleration ratio generates the overestimation bias.

Result 5: A shorter horizon of analysis on the program's effect leads to a higher overestimation bias of the seeding program's social value.

The effect of customer disadoption. Previously, when customers adopted the product, we calculated their future lifetime value at the time they adopted. This method is consistent with work on customer equity in the presence of new product growth (Gupta, Lehmann, and Stuart 2004) and in a more general sense with the new product growth literature that focuses on durables and thus considers that customer revenues materialize at the point of adoption. However, for many new products (and clearly for services), adoption is just the beginning of a relationship. For the calculation of individual lifetime value, we can indeed use a single number that takes into account the expected retention level, whereas for interconnected customers, customer expected retention has implications for the period in which they will actually affect others through word of mouth. Consequently, retention may have an effect on acceleration and expansion through the ability to provide word of mouth.

The analysis of retention effects is not straightforward, due to differing assumptions and scenarios. For example, for simplicity's sake, customer profitability researchers often use a "lost-for-good" assumption retention-wise, under which lost customers do not come back. In reality, customers may be switching back and forth among brands, which the profitability analysis should take into account to avoid a bias in the value (Libai, Muller, and Peres 2009a; Rust, Lemon, and Zeithaml 2004). To fully explore retention dynamics in a competitive situation such as the one previously described, researchers must make several assumptions regarding how customers switch among brands or leave the category overall. This is beyond our article's scope.

Nevertheless, we still wanted to gain some insight into how attrition may affect the acceleration/expansion integration. We therefore examined a basic lost-for-good case, in which adopters may disadopt the category with a certain attrition probability (i.e., when consumers disadopt, they cannot be acquired again by either brand). Although the adoption equations (Equations 2 and 3) remain the same because they describe only the temporal probability of adoption, at each period there is a positive probability (d) that the consumer who has already adopted the product will disadopt at that particular period and thus would be lost for the purpose of word-of-mouth communications. We ran the analysis under this new condition with the attrition factor d varying between 0% and 50% and demonstrate the findings in Figure 3, Panel B, for a brand operating a random seeding program on the URV e-mail network. In line with the previous results, these results are supported by our pooled regression analysis.

We find that the retention rate indeed has an impact on the acceleration ratio and that a higher disadoption probability favors expansion over acceleration. The rationale is that the power of acceleration stems from processes that begin earlier; thus, stopping them early on has a stronger effect on the created social value. We expand more on this in the discussion.

Result 6. The higher the disadoption rate, the lower the acceleration ratio.

POOLED REGRESSION ACROSS NETWORKS

In the previous section, we describe the effect of differing factors on the role of acceleration and expansion, observing a consistent picture across various types of networks. We still question to what extent the results hold when all variables are taken together in all networks, controlling for network structure parameters. In the following analysis, we deal with this issue by focusing on the factors that affect the acceleration ratio, using a pooled regression across networks.

We constructed an experimental design of the growth of two competing products in a market described by our main model (Equations 1–3). Thus, we have 12 networks; four seed types (no program, a random seeding program, and two influential seeding programs, hubs and experts); two planning horizons—the number of periods for which the program runs (15 or 30); two discount rates (10% and 15%); four values each of the external and internal coefficients (δ and q); six values for the seed size ranging from .5% to 5%; two levels of brand strength of the focal brand; and two attrition levels (0 and 20%). Note that due to computational limitations, some of our variables are dichotomous; yet this enables us to observe the difference in the effect on acceleration ratio between a lower value and a higher value of the variable. To control for the stochastic nature of the process, we ran each set of parameters 20 times, as we did previously in our standard simulations. Thus, the full factorial for the parameters was 9600 values that we ran 20 times for each of the 12 networks for a total of more than 2 million runs.

We ran a pooled regression for the 12 networks in which the dependent variable is the log of acceleration ratio (AccRatio) and the explanatory variables are the characteristics of the network and the firm. The network characteristics included network size (Size), average degree (Degree), and clustering coefficient (Cluster). We also tried average separation as another network characteristic, but because it was highly correlated with the other three network characteristics (e.g., .6 with network size), we deleted it from the regression. The firm's characteristics included the discount factor (Discount), planning horizon (Horizon), seed size (Seed), attrition rate (Attrition), and relative strength of Brand A (Strength). The resultant regression equation is the following, in which index j denotes the three seeding types: random seeding and two influential seeding, hubs and experts:

$$\text{AccRatio}_j = \alpha_{1j}\text{Size} + \alpha_{2j}\text{Degree} + \alpha_{3j}\text{Cluster} + \alpha_{4j}\text{Discount} + \alpha_{5j}\text{Horizon} + \alpha_{6j}\text{Seed} + \alpha_{7j}\text{Attrition} + \alpha_{8j}\text{Strength} + \varepsilon_j.$$

The results of the regression for the influential-hubs seeding program appear in Table 4. The other two results tables for random and influential-experts seeding programs are similar and appear in Web Appendix E (www.marketingpower.com/jmr_webappendix), in which we also report the correlation matrix for the independent variables. The results lend consistent support to our main propositions that deal with acceleration ratio. In Table 4, the seed size coefficient is negative. Because the dependent variable is acceleration ratio (i.e., the proportion of the total gain in customer equity attributable to acceleration), it follows that the larger the seed size, and thus the more powerful the program, the greater the share of the additional value of the program that is generated through acquisition rather than acceleration (consistent with Result 1).

Observe in Table 4 that the brand strength coefficient is positive. Thus, the stronger a brand is relative to its competitor, the greater the share of its seeding program's social value driven by acceleration (consistent with Result 2). We also observe in Table 4 a positive coefficient for the discount factor; thus, the higher the discount rate, the higher the program's acceleration ratio (consistent with Result 4). The attrition rate coefficient in Table 4 is negative; thus, the higher the disadoption rate, the lower the acceleration ratio (consistent with Result 6). With respect to the network characteristics, we observe in Table 4 that average degree and clustering coefficient are both negatively correlated with the acceleration ratio. This means that the denser the network connections are (i.e., the larger the average degree and the higher the clustering), the more the seeding program's profit is based on market expansion. The reasoning is that when the information flow is stronger, the program can acquire more customers and there is less need for acceleration.

DISCUSSION

We identify two major approaches for the measurement of the value of word of mouth, particularly as it occurs in seeding programs. The first approach focuses on how many people are affected, largely disregarding their actual monetary value and the question of when they are affected (Hinz et al 2011; Kempe, Kleinberg, and Tardos 2003; Watts and Dodds 2007). The second approach, in the spirit of the innovation diffusion modeling, assumes that eventually the entire target market adopts and the profit results from the acceleration of adoption due to the time value of money (Ho et al. 2012; Hogan, Lemon and Libai 2003; Jain, Mahajan, and Muller 1995; Valente and Davis 1999). Both approaches generally assume a single seller and largely avoid the issue of competition and its effect on the value of word-of-mouth campaigns.

The issue we investigate here is the way the two effects integrate to create the seeding program's actual value. Our first contribution highlights that, under competition, this integration is fundamental to the value that word-of-mouth programs create. The time value of money is indeed a prerequisite for measuring customer equity and the base with which to assess the value of any marketing initiative. For new products, the adoption horizon is long enough so that timing will have a direct effect on the bottom line. Conversely, in the presence of competition, the assumption that everyone will eventually adopt the product simply does not hold. The seeding program will not only accelerate but also expand the market; that is, it will lure otherwise nonbuyers away from the competition.

Rust, Lemon, and Zeithaml (2004) show that when considering the lifetime value customers create through their purchases, disregarding the competitive dynamics can bias both the value estimation and researchers' understanding of how value is created. Similarly, our results regarding the way competition changes the mechanisms of value creation in word-of-mouth programs highlight that extant research has paid limited attention to the matter.

This study's second contribution is its presentation of a way to measure created social value. Our approach is based on the use of agent-based models to compare the customer equity created with and without the program, following the differential effect of acceleration and expansion. The first advantage of agent-based models is that they can capture the social network structure in which the phenomenon occurs. Second, they enable researchers to follow complex phenomena through customer interactions, such as when a firm accelerates a customer, who further helps market expansion of other customers, who will in turn accelerate other customers, and so on. Agent-based models help untangle this complex chain and come closer to assessing the actual value of word-of-mouth programs. Recent work has highlighted the considerable contributions agent-based models can provide to understand complex marketing phenomena (Rand and Rust 2011), and we believe this is a good case for such contributions.

Given the measurement of the phenomenon, our third contribution is the exploration of acceleration versus expansion, which can help managers and researchers understand their seeding programs' magnitude and sources of value under different market scenarios. Our results suggest that for two similar firms under conventional market conditions across network types, expansion contributes more to the value when compared with acceleration (approximately 70% expansion vs. 30% acceleration in the networks we analyzed), though this ratio can vary greatly under different market conditions.

The underlying theme we observe is that to understand the influence of market conditions, researchers should carefully study the role of time in the process of events following the seeding action. Time is a factor for the acceleration of some consumers; through their word-of-mouth communications, new customers are acquired as well. The events that occur earlier in the process will have a more pronounced effect on the roles of acquisition and expansion than events that occur later on.

Price Decline and the Dominance of Acceleration

Declining prices and markups are a common phenomenon in a product's life cycle, causing a decrease in customer profits. This decrease in profitability is a sound demonstration of the temporal effects in seeding campaigns. We find that the lower the future customer profit per adoption (which we operationalize using a changing discount rate), the greater the effect of acceleration. The bottom line: when the near future is more important, acceleration becomes more important.

Influentials as Accelerators

One of the fundamental questions in the targeting of seeding programs relates to the contribution of influentials compared with others. We highlight an unexplored role of influentials as accelerators: acceleration drives a higher proportion of influential programs' social value relative to random programs.

Consider the role of time in this targeting decision: When a person is more influential, the incentive to accelerate his or her purchase is much higher because the chain of contagion that he or she sets off begins much earlier and is therefore longer. In addition, because the firm attracts several influentials in the seeding campaign, their spheres of influence might overlap, and this overlap would increase as the diffusion (and time) progresses, due to second- and third-degree "infections" that would have more chances to overlap. Thus, influentials' superior influence compared with random seeding is most obvious early in the process. However, in early periods, the people they infect are most likely to be accelerated consumers; because they adopted in the beginning of the process, they would have had greater chance of being infected by someone else later on.

Retention and the Power of Acceleration

The role of retention rate is also a good demonstration of time's fundamental role in value creation. There are two benefits of acceleration or expansion. One stems from the money gained from the focal person the seeding program has accelerated or acquired. In this benefit, expansion is often stronger because the firm accrues the full value of a consumer, not just the difference that stems from the earlier time of adoption. The other benefit of acceleration and expansion is their effect on the social value of others. Here, acceleration may dominate because the effect on others begins earlier, which means a stronger effect over time.

Because the attrition type we implemented happens after adoption (when the value of consumers is claimed), the role of attrition centers on its effect on others. Here, because acceleration has a stronger role to begin with, there is more to lose. That is why acceleration is more sensitive to the retention rate. However, note that the result may change if we consider other forms of retention. It is worthwhile to observe, for example, how migration among brands will affect the role of attrition on the acceleration ratio. We leave this intriguing question, part of a deeper exploration of the effect of attrition on customers' social value, for further research.

Brand Strength and Acceleration

Consider the role of the strength of the brand that creates the seeding program. We found that the stronger the focal brand, the higher the acceleration ratio of its seeding program. The idea here is that the stronger the brand is relative to its competitor, the closer it is to a monopoly and the less its need for a seeding program to cope with competition. In such a case, the stronger seller depends more on the temporal effect, accelerating the adoption of customers the firm would gain regardless. Note that with a monopolist, all of a seeding program's benefits result from acceleration, as the entire market would have adopted by the end of the time horizon.

LIMITATIONS AND FURTHER RESEARCH

Although this article focuses on the social value word-of-mouth programs generate, other types of social influence may play important roles in the contagion processes that characterize new product growth (Peres, Muller, and Mahajan 2010; Van den Bulte and Lilien 2001; Van den Bulte and Stremersch 2004). Network externalities, for example, may affect growth and customer equity differently than word of mouth (Goldenberg, Libai, and Muller 2010). Recently, researchers have begun exploring customers' indirect values in two-sided markets in which network externalities play an important role (Gupta, Mela, and Vidal-Sanz 2006). Researchers can further explore this avenue using the agent-based model and social value approach. In addition, we did not explore whether the direction of communication between nodes or the tie strength affects social value. Increasing network data availability should make this information available to researchers and serve to fine-tune our results.

Using a basic lost-for-good disadoption case, we observed that customer retention plays a role in the way acceleration and expansion create social value of seeding programs. More analysis is necessary to explore retention effects under brand-switching scenarios. Another assumption that can be relaxed is that of similar lifetime value for all customers. Companies can strategically use seeding programs to attract customers in areas of higher expected customer lifetime value. It would be worthwhile to examine how such attempts affect the contribution of acceleration and expansion. An additional issue is that expansion does not need to come at the expense of another brand. If word of mouth creates social processes that reach customers who otherwise would not have purchased even in the long run, it actually increases market potential. Even in the case of a single seller, we can view such customer acquisitions as expansion. Here, we followed classical diffusion modeling that assumes a fixed final potential. However, moving to a dynamic potential can have significant implications for the role of acceleration and expansion.

Researchers can also expand the analysis of the type we presented previously in the pooled regression. Because one of the aims of such an analysis is to capture the effect of network structure, ideally, it would run on a much larger number of network structures. We used "high" and "low" levels on some variables, but future analyses can use more levels and additional variables. We believe that increased computational power will make comprehensive analyses of large scale networks more common and enable a wider view of the complex dynamics that emerge in such networks.

In a recent review of the customer networks literature, Van den Bulte (2010) points out the difficulty of assessing the value of a consumer who is a part of a network. He argues that the intercustomer tie's complex dynamics render any straightforward analysis difficult to perform and leave researchers far from a satisfactory solution. One possible way to accomplish this is to generate a large number of distinct simulated networks using agent-based models in which researchers can gradually change the parameter and learn about this complex issue. Although a great deal of work is still needed to understand the precise mechanisms that generate social value and their implications on managerial decisions, we hope this study constitutes a significant step toward this goal.

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