

# **Decomposing the Value of Word-of-Mouth Seeding Programs: Acceleration vs. Expansion**

**Barak Libai**

Arison School of Business  
Interdisciplinary Center, Herzliya, Israel 46150

[libai@idc.ac.il](mailto:libai@idc.ac.il)

**Eitan Muller**

Stern School of Business  
New York University, New York, NY 10012

Arison School of Business  
Interdisciplinary Center, Herzliya, Israel 46150

[emuller@stern.nyu.edu](mailto:emuller@stern.nyu.edu)

**Renana Peres**

School of Business Administration  
Hebrew University of Jerusalem, Jerusalem, Israel 91905

[peresren@huji.ac.il](mailto:peresren@huji.ac.il)

October 2012

Forthcoming, *Journal of Marketing Research*

The authors would like to thank Brad Fay, Ed Keller and the Keller-Fay Group; Dr. Michael Wu and Lithium Technologies; Ted Smith and CNET; Gal Oestreicher-Singer, Shachar Reichman, Thomas Valente, and Christophe Van den Bulte for graciously supplying us with data in addition to support and helpful advice throughout this project. We would also like to thank Roland Rust, an AE and three reviewers, Pete Fader, David Godes, and Raghuram Iyengar, who contributed insightful comments and suggestions. This research was partially supported by the Institute for Business Research of Tel Aviv University; the Kmart International Center for Marketing and Retailing; the Davidson Center of Hebrew University; and the Israel Science Foundation.



# Decomposing the Value of Word-of-Mouth Seeding Programs: Acceleration vs. Expansion

## Abstract

In word-of-mouth seeding programs, customer word of mouth can generate value through market expansion, i.e. getting customers who would not otherwise have bought the product, or accelerating the purchases of customers who would have purchased anyway. Here we present the first investigation of how acceleration and expansion combine to generate value in a word-of-mouth seeding program for a new product.

We 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. We 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. We show how expansion and acceleration integrate to create the social value of programs, and 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

# 1. Introduction

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 about a million and a half potential customers (Rosen 2009).
- In 2008, Hewlett-Packard gave 31 leading bloggers the new HP Dragon laptop so as 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 Windows 7. Microsoft estimated that 7 million people may have been eventually reached by the information stemming from those parties (McMains 2010).
- In 2009, Ford gave 100 bloggers each a new Ford Fiesta, so that they would 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 accurately measure their financial performance (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; Toubia, Stephen, and Freud 2009; Schmitt, Skiera, and Van den Bulte 2011), there is still a need to better understand how these programs' monetary value is generated.

There are two main approaches in the literature for the measurement of the value of word of mouth. One approach focuses on how many new people are affected, and disregards the question of the time at which they are influenced (Watts and Dodds 2007; Hinz et al 2011). The second approach assumes that the profit comes from the acceleration of adoption of eventual adopters (Jain , Mahajan and Muller 1995; Hogan, Lemon and Libai 2003; Ho et al 2012). Yet as

we show here, the value of seeding programs, in particular in competitive markets, is derived from the interaction of both mechanisms: *market expansion*, where the firm acquires a customer who otherwise would not have purchased the brand; and *customer acceleration*, where additional revenues stem from accelerated purchases of customers who would have purchased the brand in any case, but at a later time<sup>1</sup>.

In this paper we demonstrate how the integration of customer acceleration and market expansion is fundamental to the understanding the value created by word-of-mouth programs (and in fact customers' word of mouth in general). Thus, the acceleration/expansion dynamics is fundamental to answering questions such as why a stronger brand will benefit less from a word-of-mouth program; how a future decline in price or a lower retention rate should affect the benefit from the program; how targeting influential customers changes the value of a program; and how a shorter measurement horizon can 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 hence of an essential managerial importance.

To investigate these dynamics, we first define a *customer social value* metric that measures the influence of the communication of a group of customers on the brand-related customer equity over the entire social system. We then use agent-based modeling, a simulation method that is 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

---

<sup>1</sup> An analogous decomposition is used for supermarket products where the aim is to decompose the products' sales promotion "bump" into switching 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.

structures, to look, via the agent-based model, at a common situation that is consistent with the examples presented at the beginning of this section: A new product is introduced into a competitive market via a “seeding program” in which an initial group of influentials (the *seed*) receives the product early on so that their word of mouth begins to drive diffusion (Lehmann and Esteban-Bravo 2007; Libai, Muller, and Peres 2005). The seeding program’s social value consists of any surplus generated through the program that would not have been achieved in its absence. We measure the seed’s social value in various market scenarios and analyze how this social value is largely driven by either market expansion or customer acceleration, or both.

Among our main results are the following:

- **For similar brands, seeding programs’ value is dominated by market expansion.** We find that when two new similar brands are introduced into the market, one of which launches a seeding program, the majority of the long-term social value generated by the word-of-mouth program is generated via market expansion rather than acceleration.
- **Stronger brands accelerate more, yet profit less, from a program.** In the case of 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 coming from acceleration.
- **Seeding programs aimed at influential customers are driven more by acceleration.** Influential programs, where the seeding program targets the most connected or the most persuasive individuals, generate more social value on average than do programs targeted at random individuals. Relative to random programs, a larger share of influential programs’ social value is driven by acceleration.
- **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 compared to expansion.
- **Temporal profit decline is associated with a larger role of acceleration.** When profits per customer decline over the product 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 term, it overestimates the program’s contribution. This can happen due to misinterpretation of acceleration as expansion. Given the tendency of firm’s to use short term effects to conclude on the contribution of such programs, this issue is of essential importance to the valuation of the measurement of the ROI of word-of-mouth programs for a new product.

## 2. On Seeding and Expansion vs. Acceleration

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

The literature so far has overlooked the distinction between two main underlying mechanisms via 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, and 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 individual directly helped to acquire (Satmetrix 2008). However, higher degrees of separation can be taken into account (Hogan, Lemon, and Libai 2004). Kumar, Petersen, and Leone (2010) suggested distinguishing between two types of customers: For those

who would not have purchased without the word of mouth, their full lifetime value of purchases is added to the lifetime value of the referring customer. For those who would have purchased the product without the referral, 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) showed that a customer's word-of-mouth value stems from her having helped accelerate growth, while Jain, Mahajan, and Muller (1995) and Ho et al. (2012) demonstrated 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. Seeding programs are typically used to help marketers spread a new product or idea by getting a group of target customers to adopt the product early on, aiming to enhance the contagion process for other customers (Lehmann and Estaban-Bravo 2007). 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 finally the seeding strategy itself and specifically, choosing the seeded individuals.

The issue of optimal seeding has drawn much attention by researchers. While some of this research focused on the spatial aspects of seeding, i.e., in which markets to optimally seed (Libai, Muller and Peres 2005) or via which channels (Choi, Hui, and Bell 2010), a highly examined issue surrounds the profiles of the seeded individuals. The literature on customer-to-customer interactions has devoted much attention to the role of individuals (often labeled *opinion leaders*, *influentials*, or *influencers*) who have a disproportional effect on others (Iyengar, Van den Bulte,



and Valente 2011; Katona, Zubcsek, and Sarvary 2011; Nair, Manchanda, and Bhatia 2010; Trusov, Bodapati, and Bucklin 2010). Naturally, such individuals are candidates to be targets of seeding efforts.

Hence, previous research has focused on three types of individuals that are candidates for seeding targets. The first, probably the most referred to in this sense, are *hubs*, or those most connected to others (Goldenberg et al. 2009; Watts and Dodds 2007). The assumption here is that higher connectivity will lead to a larger number of others influenced. A second type of target can be labeled “persuaders”, or “experts”: those whose disproportional effect is not in audience size but in the persuasiveness of each interaction, which can stem from being generally held in high esteem by one’s peers (Keller and Berry 2003), or because one is an expert on a subject, either due to previous knowledge or because s/he is a heavy user (Iyengar, Van den Bulte, and Valente 2011). The third type is those who enjoy an advantage due to a network position that enhances their influence in the social system. Measures of such position can include betweenness to indicate a bridge between various sub networks (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. Work in computer science suggests that finding the optimal size and identity of the individuals who will form the seed is computationally very complex and thus 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 in practice, largely because they are easiest to identify given some information on connectivity. Watts and Dodds (2007) argued that hubs do not necessarily create large cascades of influence, as may be expected. Yet considerable work, both analytical (Zubcsek and Sarvary 2010) and empirical (Hinz et al. 2011) has proven the advantage of targeting hubs.

Another issue is that it is not clear that targeting a “pure” type is the best strategy. Stonedahl, Rand, and Wilensky (2010), for example, showed that while targeting hubs is a good approach for classical network structures, in a real world Twitter network, combining high degree with a network position (high clustering) yields better results.

Our focus here is not on identifying the best targeting type, but rather on understanding the process that leads the seeding program to create profitability. A number of issues should be highlighted in this regard. First, from the firm’s prospective, customer equity or the 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 also for word of mouth related impact (Goldenberg et al. 2007; Stonedahl, Rand, and Wilensky 2010). Second, the success of seeding programs has been mostly assessed based on either the final number of individuals who adopted or showed awareness (Watts and Dodds 2007; Hinz et al. 2011), or the effect of acceleration on the NPV (Jain, Mahajan, and Muller 1995), yet not on the combined effect of both. The latter is notable given that the effect of the seeding programs had been generally investigated for the case of a single firm or product, and not 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 to understanding the seeding programs’ profitability.

The rest of the paper is structured as follows. First we define the concept of the social value of a group of customers. Then we present the agent-based model setting, where we examine seeding programs, as well as the network structure data as input to the simulations. We move on to explore the fundamental role of acceleration and expansion in social value, and how

it changes under various market scenarios and in a case of managerial misclassification. We conclude with a discussion and limitations.

### **3. The Social Value of a Word-of-Mouth Seeding Program**

As a prior step to decomposing word-of-mouth value into market expansion and acceleration, we wish to describe how we define and measure an individual's word-of-mouth contribution. In the 1946 classic film *It's a Wonderful Life*, an angel helps a businessman on the verge of suicide (played by James Stewart) 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 really 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, yet 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 end up with a certain level of overall profits. This constitutes a scenario of "life without that customer's word of mouth".

Now consider an identical scenario, with the exception that this individual generates 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 individual's social value.

Note that a few terms have been used for a measure of the worth of a customer's social effect: These include *referral value* for value generated via referral programs; *influencer value*

for non-incentivized word of mouth (Kumar et al. 2010); *indirect value* (Hogan, Lemon, and Libai 2003); *influence value* (Ho et al. 2012); and *word-of-mouth value* (Wangenheim and Bayón 2007). While 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 solely 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).

The social value of a seeding group should be calculated by assessing, at the social-system level, the monetary results achieved when the seeding group adopts a product early on, and hence starts spreading word of mouth early, and then comparing those results with those achieved in the absence of the seeding program, when the group members adopt like any other member of the social system. Starting from 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. One can assume either a durable product with a one-time purchase, or a repeat-purchase product whose value is the estimated lifetime value. Looking at 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 generated by the  $g$  customers' purchases, and the **social value**  $V_{social}(g)$ , which is the total dollar value generated by the  $g$  customers' effect 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 instead of at later times. The added value of the program, denoted by  $\Delta V_{total}^*(g)$ , is the difference in customer equity, i.e., 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 two sources:

- The direct value: The early adoption by the  $g$  customers generates value because of the time value of money. If initially the  $g$  customers' direct value was  $V_{direct}(g)$ , now it is the sum of their purchases at time zero, denoted by  $V_{direct}^*(g)$ . Therefore the program's marginal direct value is  $\Delta V_{direct}^*(g) = V_{direct}^*(g) - V_{direct}(g)$ .
- The social value: The program's marginal social value  $\Delta V_{social}^*(g)$  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 the social value of a program is given in Equation 1:

$$(1) \Delta V_{social}^*(g) = \Delta V_{total}^*(g) - \Delta V_{direct}^*(g) = V_{total}^*(N) - V_{total}(N) - (V_{direct}^*(g) - V_{direct}(g))$$

The costs of a seeding program can be divided into two components: a) The administrative costs of locating and approaching the target market and the logistical costs of handling and shipping, and b) The lost revenues that accrue from the fact that these seed consumers who are given the product for free under the seeding regime, would have purchased the product at some time during its lifetime in the no-program regime. Given no data on the administrative costs, we do not take them into account. With respect to the lost revenues, since we do run the simulation under the no-program regime, we do know the purchase time and thus the net present value of the lost revenues, which we add to the benefit from the seeding program (alternatively we could have subtracted them from the benefit of the no-program case).

#### **4. An Agent-Based Model of a Seeding Program**

Finding the social value of a seeding program requires the comparison of the customer equity of the brand in two would-be worlds – one with the program, and the other without. To do so, we use stochastic cellular automata, an agent-based modeling technique that simulates aggregate consequences based on local interactions among individual members of a population (Goldenberg, Libai, and Muller 2001). As Rand and Rust (2011) noted, looking at new products,

the patterns of growth in the market that result from the interaction of many consumers might be much more complex than the adoption rules of these individuals. The advantage of the agent-based approach is that modeling is done at the individual level and does not require knowledge of or assumptions regarding the macro-dynamics. As a result, agent-based models are increasingly being used in the marketing literature, particularly in new product growth (Delre et al. 2010; Garber et al. 2004; Shaikh, Rangaswamy, and Balakrishnan 2006; Garcia 2005).

Given the increased use of agent-based models in marketing, Rand and Rust (2011) recently introduced detailed guidelines on how to use and validate them in this context. In Web Appendix A, we present more details on the basic approach of our agent-based model, and elaborate on its consistency with the two main criteria suggested by Rand and Rust (2011) - *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 participating individuals.

### **Social network structure**

Given the increasing accessibility of social network data, a promising yet still underutilized approach is to use real-life network data to design the social structure that forms the basis 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 all these networks only as examples of real-life connectivity structures, and do not relate to any of their other specific aspects. Next we provide a short description of the networks; more details are available in Web Appendix B.

Papers have been published on three of the social networks (Networks 1–3), and their data were graciously given to us by their authors. 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 PGP (Pretty-Good-Privacy) 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). Data on six additional networks (Networks 4–9) were collected specifically for this study thanks to collaboration with Lithium Technologies, a leading provider of Social CRM solutions that power enterprise customer networks for major US and global brands. These six networks were obtained from online communities of major national brands in four industries: technology, entertainment, retail, and services. In these online communities, members communicate about the product markets and brands and discuss issues such as ideas for new products and solutions to brand-related problems. Data on Network 10 was obtained from YouTube, which while widely known as a media site, also operates as a social network for users who upload videos. The social network we present here reflects ties among 4,000 members of the YouTube social network.

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 two networks, we constructed a randomly assigned social network of 1,000 units based on 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. Data on 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 the social network literature (e.g., see Newman 2003 and Van den Bulte and Wuyts 2007). These parameters include the *size* of the network (number of nodes); *average degree*, or number of members in direct contact, both for the entire population and for the 10% of members with the most connections; *average separation*, or the average distance of each member from the rest of the network; and 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 presented here have a single major component, i.e., they are nearly free of isolated units or isolated clusters. While 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 begin 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, adopted Brand A, or adopted Brand B. As per classical diffusion modeling, the transition from potential adopter to adopter depends on two factors: *external influence*, represented by the probability  $\delta$  that an individual will be influenced by sales people, advertising, promotions, and other marketing efforts, and adopt the brand; and *internal influence*, represented by the probability  $q$  that during a given time period, an individual will be



affected by an interaction (word of mouth, or imitation) with a single other 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. 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 looked at a Uniform distribution where the range is plus minus the standard deviation used in the Normal distribution analysis. We found that the results reported next are robust to the specification of  $q$ . It should be noted that  $q$ 's heterogeneity, coupled with the range of parameter values for the advertising coefficient ( $\delta$ ) somewhat mitigates the probability of transmitting word of mouth being 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), past research has operationalized the status shift of an individual  $i$  at time  $t$  from non-adopter to adopter as a cascade of influences, where 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:

$$p_i(t) = 1 - (1 - \delta)(1 - q_i)^{N_i(t)}, \text{ where } N_i(t) \text{ is the number of adopters in } i\text{'s personal social network.}$$

We now take this model and extend it 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 individuals first adopt the category and then choose a brand, our approach is consistent with most of the diffusion literature, and specifically with brand-level models that have demonstrated a good fit to

empirical data (Libai, Muller, and Peres 2009a, 2009b). Assume two brands,  $A$  and  $B$ , each having its own external influence,  $\delta_A$  and  $\delta_B$ ; and internal influence  $q_{iA}$  and  $q_{iB}$  for each individual in the network. Adopters of  $A$  and  $B$  independently influence a potential adopter  $i$  to consider their respective brands. The probability of  $i$  being successfully influenced to consider brand  $A$  or  $B$  by at least one adopter of  $A$  or  $B$  is given by:

$$(2) \quad p_i^A(t) = 1 - (1 - \delta_A)(1 - q_{iA})^{N_i^A(t)}$$

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

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 given by  $p_i^A(1 - p_i^B)$ . Having thus being influenced by  $A$  but not 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 as per the ratio of probabilities  $\alpha$ . Therefore, the probabilities of  $i$  adopting  $A$ , or  $B$ , or neither are given respectively by the following:

$$P_i(\text{adopt } A) = p_i^A(1 - p_i^B) + \alpha_A p_i^A p_i^B; \quad P_i(\text{adopt } B) = p_i^B(1 - p_i^A) + \alpha_B p_i^A p_i^B$$

$$P_i(\text{adopt none}) = (1 - p_i^B)(1 - p_i^A); \quad \text{where } \alpha_A = \frac{p_i^A}{p_i^A + p_i^B}, \quad \alpha_B = 1 - \alpha_A$$

In the simulation, the adoption probability's realization was performed through 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  $\delta$ ,  $q$ , and the number of periods vary between simulations, and their ranges were chosen so as to be consistent with previous research regarding  $\delta$ 's and  $q$ 's ranges in diffusion models and in agent-based models (e.g., Goldenberg et al. 2007).

The parameter ranges are summarized in Table C1 in Web Appendix C. 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 are such that most of the market has adopted by that time and thus the market potential is in most cases fully tapped. Given in addition the discount factor, any additional profitability added beyond 30 periods is negligible. Lastly, the simulations were programmed in C++ and the pseudo-code is available in Web Appendix D.

### **The seeding program and measurement of social value**

We use a seeding program in which a selected group of individuals initiates the diffusion process in the network. We vary 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 0.5% to 5% of the potential market. The second issue is who to target as program members. As discussed earlier, while the firm might seed randomly, it can also target influential customers of two types: Those who have a large number of connections (hubs), and those who exert inordinate influence over others (experts). Hence we consider three groups:

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

We drew a new group of seed members for each simulation. In order 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 explained above, we define the 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 measure the customer equity for a brand, which is the sum of the discounted cash flow from all adopters over all the time periods. We assume that each adopter contributes a normalized value of 1 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 use a discount rate of 10% per time period (e.g., Goldenberg et al. 2007). We will later examine the effects of changing the value of future cash flows.

## **5. 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 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. Since 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 the differences are attributed to changes in the program rather than to random fluctuations. To avoid stochastic effects of a single run, each combination of parameters in each network was run 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: differential brand strength and declining profits. Lastly, we report the effect of biases created by misspecification of market conditions: considering a short time horizon, and ignoring disadoption. In this section we demonstrate the results considering one factor at a time and one network at a time. In section 6 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**

The roles of acceleration and expansion in seeding programs are presented in this section: Table 2 presents detailed results for the Keller-Fay network, while Table 3 summarizes the main results for the 12 networks. In order to explain the results of Table 3, observe the example in Table 2 (column 1): if Brand A begins a random seeding program, its average equity increases from a value of about 225 (in the “no seeding program” scenario) to 375, a gain of about 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.

Since 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 looking at the scenarios with and without a program, and track 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 to no program) attributable to customer acceleration (columns 3 and 4 of Table 3). Interestingly, the acceleration ratio can also be computed from the aggregate results, as we illustrate via the Keller-Fay example in Table 2. When only Brand A operates a random program, Brand A’s customer equity increases by about \$150 ( $=375.5 - 225.3$ ), whereas Brand B’s customer equity decreases by \$97 ( $=127.9 - 224.8$ ). Since we assume only two competitors and no outside option (by the end of the time horizon virtually the entire market adopt the

product) it follows that A gained what B lost, and thus 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%.

Looking at columns 3 and 4 in Table 3, we see that most of the social value generated by the seeding program derives from market expansion. On average, acceleration ratio is 26% for the case of a random targeting, and 32% and 28% for influential targeting, hubs, and experts, respectively. In all cases, the acceleration ratio is well below the 50% level. The results in Table 3 are largely consistent across various networks, even though the networks themselves vary greatly in their basic characteristics (Table 1). The role of acceleration is also related to the program's profitability: We see a correlation of 0.7 for a random program and 0.6 for an influential program, between the percentage of market expansion and the profitability of the program, indicating that most value added comes from market expansion.

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

### **Influential vs. random programs**

From Table 3 we observe that the results we obtain are generally consistent for both random and influential programs, yet magnitude varies. It is interesting to better understand how acceleration and expansion affect the difference between the two cases. Before that, an interesting observation stemming from Table 3 is that of the total social value generated by an influential-hubs seeding program in the networks we analyzed, 77% on average could be achieved by a random program. Similarly for influential-experts seeding that was found to be more effective than random seeding but less than influential-hubs seeding (consistent with Hinz

et al. 2011)<sup>2</sup>. Marketers can derive differing conclusions here, one of which might be that most of the program's value can be gained without having to identify and affect influentials.

Alternatively, if one is able to reach influentials (hubs), it can raise the social value by an additional 30% over a random seeding program.

Does the seeding target affect the roles of acceleration and expansion? From the last two columns of Table 3, we can see 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. It is simple to show that the social value generated by acceleration in influential programs is on average over 70% higher than that generated by acceleration in random programs. Thus, as random programs do a good job of acquiring customers from the competition, the extra connectivity of the influencers has limited additional effect in that sense. What influencers can do better, however, is enhance the acceleration of future customers.

**Result 2: Relative to random programs, a higher proportion of influential programs' social value is driven by acceleration.**

### **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 where per-customer profits decline with time.

---

<sup>2</sup> This is the one place where the shape of the distribution of  $q$  matters. While the order of efficiency: influential-hubs; influential-experts; and random was found under both the Normal and Uniform distributions, in Power-Law distribution, influential-experts seeding was found to be more effective than influential-hubs.

### *Differing brand strength*

While our previous analysis focused on the competition between two similar brands, the issue of the effect of brand strength on expansion and acceleration is discussed next. We ran an additional simulation, this time with Brand A's  $\delta$  and  $q$  values higher than those of Brand B. The difference in brand strength is operationalized by a parameter  $k$  that multiplies the communication parameters  $q$  and  $\delta$ , and therefore represents the brand's relative strength: If  $k = 2$ , for example, it means that Brand A's  $\delta$  and  $q$  values are twice those of Brand B, and thus Brand A is twice as strong in terms of adoption. Hence,  $k = 1$  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. The results for the Entertainment 1 Lithium network and an influential–experts seeding program are illustrated in Figure 2.

The stronger Brand A is (in terms of  $\delta$  and  $q$ ) relative to Brand B, the lower the social value and the higher the acceleration value of Brand A's seeding program. One way to see this is that 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. Similar results are obtained 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 its seeding program's social value is driven by acceleration, and the lower the program's social value overall.**



### *Declining profits*

In the above analysis, we assumed that future customers generate the same lifetime value as do current ones, with the only difference stemming from the 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). An interesting question is to what extent this phenomenon might change the dynamics reported thus far. Although price is not an explicit part of our model, we can still examine the question 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, this means that future customers have a lower future monetary value, similar to the effect of a higher discount rate.

Figure 3 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 above, we considered discount rates of 5%, 8%, 12%, 15%, and 20%. The figure displays three curves: First is Brand A's overall profit gain, achieved by implementing a random seeding program, compared to 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 the temporal dimension of seeding programs: On one extreme, when the discount rate is zero, the firm cares only about acquiring customers, regardless of when they are acquired, and 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 about \$16. The same purchase at period 4 is worth about \$48 today and thus accelerating this customer purchase six period ahead results net gain of about \$32. Thus with such high discount rate expansion is worth about half of acceleration for this specific consumer. Note that this is just the monetary benefit and does not include the extra benefit from the earlier word-of-mouth activity of the accelerated purchase. Thus the lower is future customers value (either because of falling prices or because of a high discount factor), the greater is the effect of acceleration. The social value of a seeding program also increases since 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**

In this subsection we investigate the effects of two potential misspecifications commonly found in the market: Using short time horizon for profitability calculation, and ignoring disadoption.

#### *The bias of a short time horizon*

In the analysis of Tables 3 and 4, we looked at 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 a certain number of periods after launch to its expected effect without a program. Would such action change the results we saw above, and can the expansion / acceleration dynamics help us to explain the result? To explore this issue, we re-ran the model for the 12 networks, this time stopping the simulation at

certain points along the way and examining the results. We present next the results for the Keller-Fay network and in Table C2 of Web Appendix C for the rest of the networks.

Figure 4 shows how the social value and acceleration ratio of a brand operating an influential-hubs seeding program on High-tech 1 Lithium is changing when various time horizons are used. The final long-term ratio is that reached after 30 periods. We see that early on, Brand A considerably overestimates the program's contribution. A manager checking the program's social value after five 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 true, actual, long-term gain. That is, measuring the program's value after five periods would lead to a considerable overestimation. The reason is that when comparing the scenario with the program to the scenario without the program, many of those who adopted at the short time interval who are counted as expansion due to the program, 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 overestimation bias is generated due to the underestimation of the acceleration ratio.

**Result 5. A shorter horizon of analysis on the program's effect, will lead to a higher overestimation bias of the seeding program's social value.**

#### *The effect of customer disadoption*

So far, when a customer adopted the product, we calculated her future lifetime value at the time s/he adopted, 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 focused on durables and thus considered customer revenues as materializing at the point of adoption. However, for many new products, and clearly for services,

adoption is just the start of a relationship. While for the calculation of individual lifetime value one can indeed use a single number that takes into account the expected retention level, for interconnected customers, customer expected retention has implications for the period in which they will actually affect others via word of mouth. Hence, retention may have an effect on acceleration and expansion via the ability to provide word of mouth.

The analysis of retention effects is not straightforward due to differing assumptions and scenarios that should be examined. 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 should be taken into account in the profitability analysis to avoid a bias in the value (Rust, Lemon, and Zeithaml 2004; Libai, Muller, and Peres 2009a). Clearly, in order to fully explore retention dynamics in a competitive situation such as the one here, one needs to make several assumptions regarding how customers switch among brands, or leave the category overall. This is beyond our scope here.

Yet we still wanted to gain at least some insight into how attrition may affect the acceleration / expansion integration. We therefore looked at a basic Lost for Good case, in which adopters may disadopt the category with a certain attrition probability (i.e., when one disadopts, they cannot be acquired again by either brand). While the adoption equations (2 and 3) remain the same, since 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 the findings are demonstrated in Figure 5 for a brand operating a random seeding

program on the URV e-mail network. As in the previous results, these results are supported by our pooled regression analysis presented next.

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

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

## 6. Pooled Regression Across Networks

In the previous section we described the effect of differing factors on the role of acceleration and expansion, observing a consistent picture across various types of networks. The question can be still asked, 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 looking at 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 through 3). Thus we have 12 networks; four seed types (no program, a random seeding program and two influential seeding: hubs, and experts); two planning horizons, i.e., 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 ( $\delta$  and  $q$ ); six values for the seed size ranging from 0.5% 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 it enable us to see 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 9,600 values that we ran 20 times each for each of the 12 networks for a total of more than two million runs.

We ran a pooled regression for the 12 networks where 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 as it was highly correlated with the other three network characteristics (e.g., 0.6 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, where index *j* denotes the three seeding types: random seeding and two influential seeding – hubs and experts:

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

The results of the regression for the influential–hubs seeding program is given in Table 4. The other two results tables for random and influential–experts seeding programs are very similar and reported in Web Appendix E, where 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. Since 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 via 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 the social value of its seeding program that is driven by acceleration, consistent with Result 2. We also observe in Table 4 a positive coefficient for the discount factor, and thus the higher the discount rate, the higher the program's acceleration ratio, as per Result 4. The attrition rate coefficient in Table 4 is negative, and thus the higher the disadoption rate, the lower the acceleration ratio, as per Result 6. With respect to the network characteristics, we observe in Table 4 that average degree and clustering coefficient are both negatively correlated to the acceleration ratio. This means that the denser the network connections are — the larger average degree and higher clustering — the more the seeding program's profit is based on market expansion. The reasoning is that when the information flow is stronger, more customers can be acquired by the program, and there would be less need for acceleration.

## **7. Discussion**

One can identify two major approaches for the measurement of the value of word of mouth, and in particular seeding programs. One approach focuses on how many people are affected, and largely disregards their actual monetary value and the question of *when* they are affected (Watts and Dodds 2007; Kempe, Kleinberg and Tardos 2003; Hinz et al 2011). The second approach, in the spirit of the innovation diffusion modeling, assumes that eventually all of the target market adopts and the profit comes from the acceleration of adoption due the time value of money (Jain ,Mahajan and Muller 1995; Hogan, Lemon and Libai 2003; Ho et al 2012,

Valente and Davis 1999). Both approaches have generally assumed a single seller and largely avoided the issue of competition and its effect on the value of word of mouth campaigns.

The issue we investigate here is the manner in which the two effects integrate to create the actual value of the seeding program. Our first contribution is to highlight that under competition this integration is fundamental to the value created by word-of-mouth programs. The time value of money is indeed a prerequisite for measuring customer equity, the base to assessing the value of any marketing initiative. In the case of new products the adoption horizon is long enough so that timing will have a direct effect on the bottom line. On the other hand, in the presence of competition, the assumption that everyone eventually adopts our product simply does not hold. The seeding program will not only accelerate but also expand the market, that is, it will attract otherwise non-buyers away from the competition.

It had been shown in the past that when considering the lifetime value customers create through their purchases, disregarding the competitive dynamics can bias the value estimation and our understanding of how value is created (Rust, Lemon and Zeithaml 2004). In a similar manner, our results regarding the way in which competition changes the mechanisms of value creation in word of mouth programs highlight the limitation of current research that historically gave limited attention to the matter.

The second contribution of this study is to present a way to measure the social value created. 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. One advantage of agent-based models is that they can capture the social network structure in which the phenomenon occurs. Second, they allow researchers to follow complex phenomena based on customer interactions, such as the case that occurs when a firm accelerates



a customer, and this customer further helps market expansion of other customers, that will further accelerate other customers, and so on. Agent-based models help us to untangle this complex chain, and come closer to assessing the real value of word-of-mouth programs. Recent work has highlighted the considerable contribution agent-based models can provide to understand complex marketing phenomena (Rand and Rust 2011) and we believe this is a good case for such contribution.

Given the measurement of the phenomenon, the third contribution is the exploration of drivers of acceleration vs. expansion, which can help managers and researchers understand the magnitude and sources of value of their seeding program under different market scenarios. Our results suggest that across network types, for two similar firms under conventional market conditions, expansion contributes more to the value compared to acceleration (about 70% expansion to 30% acceleration in the networks we analyzed), yet this ratio can largely change under different market conditions.

The underlying theme we see is that in order to understand the influence of market conditions, one should carefully study the role of time in the process of events that follow the seeding action. Time matters for the acceleration of some consumers and through their word-of-mouth communications, new customers are acquired as well. What happens early will change the role of acquisition and expansion compared to what happens late. Consider the following results reported:

**Price decline and the dominance of acceleration.** Declining prices and markups are a common phenomenon in product 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 is future customer profit per adoption (which we operationalize via a changing

discount rate) the greater is the effect of acceleration. Consider the following example to highlight the issue. On one extreme, when the discount rate is zero, the firm cares only about acquiring customers, regardless of when they are acquired, and accelerating a customer is simply not worthwhile. On the other extreme, with a high discount rate of 20%, suppose a customer buys the product in period 10 for \$100. It is straightforward to compute the current value (with 20% discount rate) at about \$16. The same purchase at period 4 is worth about \$48 today and thus accelerating this customer purchase six periods ahead results net gain of about \$32. Thus with such high discount rate market expansion is worth about half of acceleration for this specific consumer (note that this is just the monetary benefit and does not include the extra benefit from the earlier word-of-mouth activity of the accelerated purchase, which might strengthen the phenomenon). 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 as compared to others. We highlight an unexplored role of influentials as accelerators: We find that relative to random programs, a higher proportion of influential programs' social value is driven by acceleration.

Consider the role of time in this targeting decision: When an individual is more influential, the incentive to accelerate his/her purchase is made much higher since the chain of contagion that s/he begins, begins much earlier and is therefore longer. Add to that the following effect: since the firm attract a number of influentials in the seeding campaign, their sphere of influence might overlap, and this overlap would increase as the diffusion (and time) progresses because of second and third degree "infection" that have more chance to overlap. Thus their influence over and above random seeding is felt especially early on, but in early periods, the individuals they

infected are most likely to be accelerated individuals, since by adopting early on, they would have had more chance of being infected by someone else later on.

**Retention and the power of acceleration.** The role of retention rate is also good demonstration for the fundamental role of time in the value creation. Basically, one can see two benefits to acceleration or expansion. One stems from the money gained from the focal individual that has been accelerated or acquired. Here often expansion is stronger because the firm accrues the full value of an individual, not only the difference that stems from the earlier time of adoption. The other benefit is the effect on the social value of others. Here acceleration may dominate since the effect on others start earlier, which means stronger effect over time.

Because we the attrition type we implemented happens after adoption (where the value of individuals is claimed), the role of attrition centers on the contribution due to the effect on others. And here, because acceleration has a stronger role to begin with, it has more to lose. That is why acceleration is more sensitive to the retention rate. One should note though that the result may change if other forms of retention will consider. It is interesting to see how migration among brands, for example will affect the role of attrition on the acceleration ratio. We leave this intriguing question, a part of a deeper exploration of the effect of attrition on the social value of customers, to future research

**Brand strength and acceleration.** Consider the role of the strength of the brand that creates the seeding program: We found that the stronger is the focal brand, the higher is the acceleration ratio of its seeding program. The intuition here is that the stronger the brand 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 is depends more on the temporal effect: accelerating the adoption of customers the firm would gain anyhow. Note that with a monopolist,

all the benefits of a seeding program are due to acceleration, as the entire market would have adopted by the end of the time horizon.

## **8. Limitations and future research**

While we focus here on the social value generated by word-of-mouth programs, other types of social influence may play important roles in the contagion processes that characterize new product growth (Peres, Muller, and Mahajan 2009; Van den Bulte and Lilien 2001; Van den Bulte and Stremersch 2004). Network externalities, for example, may affect growth and customer equity differently than does 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). This avenue can be further explored 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 saw that customer retention plays a role in the manner in which acceleration and expansion create social value of seeding programs. More analysis is needed to explore retention effects under brand switching scenarios. Another assumption that can be relaxed is that of similar lifetime value for all customers. Seeding programs can be strategically used to attract customers in areas of higher expected CLV. It is interesting to see how such attempts will affect the contribution of acceleration and expansion. An additional issue is that expansion does not have to come at the expense of another brand. If word of mouth creates social processes that reach customers that otherwise would not have purchased even in the long run, it in fact increases market potential. Even in a case of a single

seller, such customer acquisitions can be viewed as expansion. Here we followed classical diffusion modeling that assumes a fixed final potential. However, moving to a dynamic potential can have interesting implications for the role of acceleration and expansion.

The analysis of the type presented in the pooled regression in section 6 can also be expanded. Since one of the aims of such analysis is to capture the effect of network structure, ideally the analysis would be run on a much larger number of network structures. We have used a “high” and “low” levels on some variables, yet more levels can be used, as well as additional variables. We believe that increased computational power will make comprehensive analysis 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) pointed out the difficulty of assessing the value of an individual who is a part of a network. He argued that the inter-customer 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 ABM where one can gradually change the parameter and gain intuition about this complex issue. While a great deal of work is still needed toward understanding the precise mechanisms that generate social value and their implications on managerial decisions, we hope this study constitutes a significant step toward this goal

## References

- Berger, Jonah and Eric M. Schwartz (2011), "What drives immediate and ongoing word of mouth?," *Journal of Marketing Research*, 48(5), 869-880.
- Boguña, M., R. Pastor-Satorras, and A. Diaz-Guilera (2004), "Models of social networks based on social distance attachment," *Physical Review E*, 70(5) (056122), 1-8.
- Chevalier, Judith A. and Dina Mayzlin (2006), "The effect of word of mouth on sales: Online book reviews," *Journal of Marketing Research*, 43(3), 345-354.
- Choi, Jeonghye, Sam K. Hui, and David R. Bell (2010), "Spatiotemporal analysis of imitation behavior across new buyers at an online grocery retailer," *Journal of Marketing Research*, 47(1), 75-89.
- Delre, A. Sebastiano, Wander Jager, Tammo H. A Bijmolt, and Marco A. Janssen (2010), "Will it spread or not? The effects of social influences and network topology on innovation diffusion," *Journal of Product Innovation Management*, 27(2), 267-282.
- Dunn, Lucinda (2007), "Identifying influencers in the digital age: The uploader research," in *Measuring Word of Mouth*, Vol. 3, Walter J. Carl ed., Chicago: Word of Mouth Marketing Association.
- Garber, Tal, Jacob Goldenberg, Barak Libai, and Eitan Muller (2004), "From density to destiny: Using spatial analysis for early prediction of new product success," *Marketing Science* 22(3), 419-428.
- Garcia, Rosanna (2005), "Uses of agent-based modeling in innovation/new product development research," *Journal of Product Innovation Management*, 22(5), 380-398
- Godes, David and Dina Mayzlin (2004), "Using online conversations to study word of mouth communication," *Marketing Science*, 23(4), 545-560.
- (2009), "Firm-created word-of-mouth communication: A field-based quasi-experiment," *Marketing Science*, 28(4), 721-739.
- , Yubo Chen, Sanjiv Das, Chrysanthos Dellarocas, Bruce Pfeiffer, Barak Libai, Subrata Sen, Shi Mengze, and Peeter Verlegh (2005), "The firm's management of social interactions," *Marketing Letters*, 16(3/4), 415-42.
- Goldenberg, Jacob, Barak Libai, Sarit Moldovan, and Eitan Muller (2007), "The NPV of bad news," *International Journal of Research in Marketing*, 24(3), 186-200.
- Goldenberg, Jacob, Barak Libai, and Eitan Muller (2001), "Talk of the network: A complex system look at the underlying process of word of mouth," *Marketing Letters*, 12(3), 209-221.
- (2002), "Riding the saddle: How cross-market communications can create a major slump in sales," *Journal of Marketing*, 66(2), 1-16.
- (2010), "The chilling effects of network externalities," *International Journal of Research in Marketing*, 27(1), 4-15.
- Goldenberg, Jacob, Sangman Han, Donald R. Lehmann, and Jae Weon Hong (2009), "The role of hubs in the adoption process," *Journal of Marketing*, 73(2), 1-13.

- (2010), “Social connectivity, opinion leadership, and diffusion,” in *The Connected Customer*, Stefan H.K. Wuyts, Marnik G. Dekimpe, Els Gijbrecchts, and F.G.M.(Rik) Pieters, eds., London: Routledge.
- Golder, Peter N. and Gerard T. Tellis (2004), “Growing, growing, gone: Cascades, diffusion, and turning points in the product life cycle,” *Marketing Science*, 23(2), 207-218.
- Guimera, R., L. Danon, A. Diaz-Guilera, F. Giralt, and A. Arenas (2003), “Self-similar community structure in a network of human interactions,” *Physical Review E* 68(065103R), 1-4.
- Gupta, Sunil, Donald R. Lehmann, and Jennifer Ames Stuart (2004), “Valuing customers,” *Journal of Marketing Research*, 41 (February), 7-18.
- Gupta, Sunil, Carl F. Mela, and Jose M. Vidal-Sanz (2006), “The value of a ‘free’ customer,” Harvard Business School, working paper no. 07-035.
- Gupta, Sunil, Dominique Hanssens, Bruce Hardie, William Kahn, V. Kumar, Nathaniel Lin, Nalini Ravishanker, and S. Sriram (2006), “Modeling customer lifetime value,” *Journal of Service Research*, 9(2), 139-155.
- Hinz, Oliver, Bernd Skiera, Christian Barrot, and Jan U. Becker (2011), “Seeding strategies for viral marketing: An empirical comparison,” *Journal of Marketing*, 75(3), 55-71.
- Ho, Tech-Hua, Sahn Li, So-Eun Park, and Zuo-Jun Max Shen (2012), “Customer influence value and purchase acceleration in new product diffusion,” *Marketing Science*, 31(2), 236-256.
- Hogan, John E., Katherine N. Lemon, and Barak Libai (2003), “What is the real value of a lost customer?” *Journal of Service Research*, 5(3), 196-208.
- (2004), “Quantifying the ripple: Word of mouth and advertising effectiveness,” *Journal of Advertising Research*, 44(3), 271-280.
- Iyengar, Raghuram, Christophe Van den Bulte, and Thomas Valente (2011), “Opinion leadership and social contagion in new product diffusion,” *Marketing Science*, 30(2), 195-212.
- Jackson, Matthew O. and Brian W. Rogers (2007), “Meeting strangers and friends of friends: How random are social networks?” *American Economic Review*, 97(3), 890-915.
- Jain, Dipak, Vijay Mahajan, and Eitan Muller (1995), “An approach for determining optimal product sampling for the diffusion of a new product,” *Journal of Product Innovation Management*, 12(2), 124-135.
- Katona, Zsolt, Peter Pal Zubcsek, and Miklos Sarvary (2011), “Network effects and personal influences: The diffusion of an online social network.” *Journal of Marketing Research*, 48(3), 425-443.
- Keller, Ed (2007), “Unleashing the power of word of mouth: Creating brand advocacy to drive growth,” *Journal of Advertising Research*, 47(4), 448-452.
- and John Berry (2003), *The Influentials*, New York: Free Press.
- Kempe, David, Jon Kleinberg, and Eva Tardos (2003), “Maximizing the spread of influence through a social network,” *SIGKDD '03 Washington, DC, USA*.

- Kornish, Laura J. and Qiuping Li (2010), "Optimal referral bonuses with asymmetric information: Firm-offered and interpersonal incentives," *Marketing Science*, 29(1), 108-121.
- Kumar, V., Andrew Petersen, and Robert P. Leone (2010), "Driving profitability by encouraging customer referrals: Who, when, and how," *Journal of Marketing*, 74(5), 1-17.
- Lehmann, Donald R. and Mercedes Esteban-Bravo (2006), "When giving some away makes sense to jump-start the diffusion process," *Marketing Letters*, 17(4), 243-254.
- Leskovec, Jure, Lada A. Adamic, and Bernardo A. Huberman (2007), "The dynamics of viral marketing," *ACM Transactions on the Web*, 1 (1), 1-39.
- Libai, Barak, Eitan Muller, and Renana Peres (2005), "The role of seeding in multi-market entry," *International Journal of Research in Marketing*, 22(3) 375-393.
- (2009a), "The diffusion of services," *Journal of Marketing Research*, 46(2), 163-175.
- (2009b), "The role of within-brand and cross-brand communications in competitive growth," *Journal of Marketing*, 73(3), 19-34.
- Libai, Barak, Ruth Bolton, Marnix S. Buegel, Ko de Ruyter, Oliver Goetz, Hans Risselada, and Andrew T. Stephen (2010), "Customer-to-customer interactions: Broadening the scope of word of mouth research," *Journal of Service Research*, 13 (3), 267-82.
- Liu, Yong (2006), "Word of mouth for movies: Its dynamics and impact on box office revenue," *Journal of Marketing*, 70(2), 74-89.
- Luo, Xueming (2009), "Quantifying the long-term impact of negative word of mouth on cash flows and stock prices," *Marketing Science*, 28(1), 148-165.
- McMains, Andrew (2010), "Consumers party on for major brands," *Adweek*, 51(5), accessed September 2, 2010.
- Miles, Louella (2006), "Words' worth," *Marketing*, January 25.
- Newman, Mark E.J. (2003), "The structure and function of complex networks," *SIAM Review* 45(2), 167-256.
- Nair, Harikesh, Puneet Manchanda, and Tulikaa Bhatia (2010), "Asymmetric social interactions in physician prescription behavior: The role of opinion leaders," *Journal of Marketing Research*, 47(5), 883-895.
- Peres, Renana, Eitan Muller, and Vijay Mahajan (2010), "Innovation diffusion and new product growth: Critical review and research directions," *International Journal of Research in Marketing*, 27(2), 91-106.
- Quinton, Brian (2008), "Enter the dragon," *Promo*, October 1.
- Rand, William and Roland T. Rust (2011), "Agent-based modeling in marketing: Guidelines for rigor," *International Journal of Research in Marketing*, 28(3), 181-193.
- Rosen, Emanuel (2009), *The Anatomy of Buzz Revisited: Real-life Lessons in Word of Mouth Marketing*, New York: Broadway Business.
- Rust, Roland T., Katherine N. Lemon, and Valerie Zeithaml (2004), "Return on marketing: Using customer equity to focus marketing strategy," *Journal of Marketing*, 68 (1), 109.



- Rust, Roland T. and Tuck Siong Chung (2006), "Marketing models of service and relationships," *Marketing Science*, 25(6), 560-580.
- Schmitt, Philipp, Bernd Skiera, and Christophe Van den Bulte (2011), "Referral programs and customer value," *Journal of Marketing*, 75(1), 46-59.
- Satmetrix (2008), "Net promoter economics: The impact of word of mouth," working paper.
- Shaikh, Nazrul I., Arvind Rangaswamy, and Anant Balakrishnan (2006), "Modeling the diffusion of innovations using small-world networks," working paper, Penn State University.
- Smith, Ted, James R. Coyle, Elizabeth Lightfoot, and Amy Scott (2007), "Reconsidering models of influence: The relationship between consumer social networks and word of mouth effectiveness," *Journal of Advertising Research*, 47(4), 387-397.
- Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-based assets and shareholder value: A framework for analysis," *Journal of Marketing*, 62(1), 2-18.
- Stephen, Andrew T. and Jeff Galak (2012), "The effects of traditional and social earned media on sales: A study of a microlending marketplace," forthcoming, *Journal of Marketing Research*.
- Stephen, Andrew T., Yaniv Dover, and Jacob Goldenberg (2010), "A comparison of the effects of transmitter activity and connectivity on the diffusion of information over online social networks," SSRN working paper.
- Stonedahl, Forrest, William Rand and Uri Wilensky (2010), "Evolving viral marketing strategies," GECCO proceeding of the 12<sup>th</sup> annual conference on Genetic and Evolutionary Computation.
- Tegler, Eric (2009), "Ford is counting on army of 100 bloggers to launch new fiesta," *Advertising Age*, April 20.
- Toubia, Olivier, Andrew T. Stephen, and Aliza Freud (2009), "Viral marketing: A large-scale field experiment," working paper, INSEAD.
- Trusov, Michael, Randolph E. Bucklin, and Koen H. Pauwels (2009), "Effects of word of mouth versus traditional marketing: Findings from an Internet social networking site," *Journal of Marketing*, 73(5), 90-102.
- Trusov, Michael, Anand V. Bodapati, and Randolph E. Bucklin (2010), "Determining influential users in Internet social networks," *Journal of Marketing Research*, 47(4), 643-658.
- Valente, Thomas W., Susan C. Watkins, Miriam N. Jato, Ariane Van Der Straten, and Louis-Philippe M. Tsitsol (1997), "Social network associations with contraceptive use among Cameroonian women in voluntary associations," *Social Science and Medicine*, 45, 677-687.
- Valente, Thomas W. and Rebecca L. Davis (1999), "Accelerating the diffusion of innovations using opinion leaders," *The Annals of the American Academy of Political and Social Science*, 566, 55-67.
- Van den Bulte, Christophe (2010), "Opportunities and challenges in studying customer networks," in *The Connected Customer*, Stefan Wuyts, Marnik G. Dekimpe, Els Gijsbrechts, and Rik Pieters, eds., London: Routledge.

- Van den Bulte, Christophe and Gary L. Lilien (2001), "Medical innovation revisited: Social contagion versus marketing effort," *American Journal of Sociology*, 106(5), 1409-1435.
- Van den Bulte, Christophe and Stefan Stremersch (2004), "Social contagion and income heterogeneity in new product diffusion: A meta-analytic test," *Marketing Science*, 23(4), 530-544.
- Van den Bulte, Christophe and Stefan Wuyts (2007), *Social Networks and Marketing*, Cambridge, MA: Marketing Science Institute.
- Van Heerde, Harald. J. and Scott A. Neslin (2008), "Sales promotion models," in *Handbook of Marketing Decision Models*, Wierenga, Berend, ed., vol. 121, London: Springer, 107-162.
- Van der Lans, Ralf, Gerrit van Bruggen, Jehoshua Eliashberg, and Berend Wierenga (2010), "A viral branching model for predicting the spread of electronic word of mouth," *Marketing Science*, 29(2), 348-365.
- Verhoef, Peter C. and Peter S.H. Leeflang (2009), "Understanding the marketing department's influence within the firm," *Journal of Marketing*, 73(2), 14-37.
- Villanueva, Julian, Shijin Yoo, and Dominique M. Hanssens (2008), "The impact of marketing-induced versus word of mouth customer acquisition on customer equity growth," *Journal of Marketing Research*, 45(1), 48-59.
- Wangenheim, Florian. V. and Tomás Bayón (2007), "The chain from customer satisfaction via word-of-mouth referrals to new customer acquisition," *Journal of the Academy of Marketing Science*, 35(2), 233-249.
- Wasserman, Todd (2008), "Is talk cheap? How cheap?" *Brandweek*, June 29.
- Watts, Duncan J. (2007), "The accidental influentials," *Harvard Business Review*, 85(2), 22-23.
- and Peter Sheridan Dodds (2007), "Influentials, networks, and public opinion formation," *Journal of Consumer Research*, 34(4), 441-458.
- Zubcsek, Peter P. and Miklos Sarvary (2011), "Direct marketing on a social network," *Quantitative Marketing and Economics*, 9, 71-109.

**Table 1.** Network characteristics

Network	Description	Reference	Size	Average degree	Average degree top 10%	Average separation	Clustering coefficient	
<b>Published networks</b>								
1	URV e-mail network	University e-mail network	Guimera et al. 2003	1,133	9.6	31.3	3.6	0.220
2	PGP	Software user network	Boguña et al. 2004	10,680	4.6	22.5	7.5	0.266
3	Cameroon Tontines	Cameroonian women	Valente et al. 1997	161	6.0	13.9	3.2	0.128
<b>Networks collected for this study</b>								
4	Retailer	Lithium network		4,968	8.8	60.0	3.5	0.502
5	Services	Lithium network		4,457	13.5	98.6	2.8	0.481
6	High-tech 1	Lithium network		3,574	2.6	16.4	2.8	0.145
7	High-tech 2	Lithium network		3,663	2.6	15.8	3.4	0.176
8	Entertainment 1	Lithium network		1,496	5.3	33.5	3.5	0.285
9	Entertainment 2	Lithium network		7,045	4.2	28.4	3.6	0.239
10	YouTube	Networking site		4,160	8.5	30.2	4.0	0.073
<b>Empirical-degree random networks</b>								
11	Keller-Fay	TalkTrack WOM survey	Keller 2007	1,000	6.0	17.7	5.0	0.056
12	CNET	Survey on social networks	Smith et al. 2007	1,000	42.2	106.9	2.2	0.110
<b>Average</b>				<b>3,611</b>	<b>9.5</b>	<b>39.6</b>	<b>3.8</b>	<b>0.22</b>

**Table 2.** Customer equity and number of adopters for programs targeting random customers and influentials-hubs: Keller-Fay network

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

\* Compared to 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		3. Acceleration ratio* random program	4. Acceleration ratio* influential program	
			Hubs	Experts		Hubs	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%
	<b>Average</b>	<b>80.2%</b>	<b>104.5%</b>	<b>90.6%</b>	<b>25.9%</b>	<b>31.5%</b>	<b>28.4%</b>

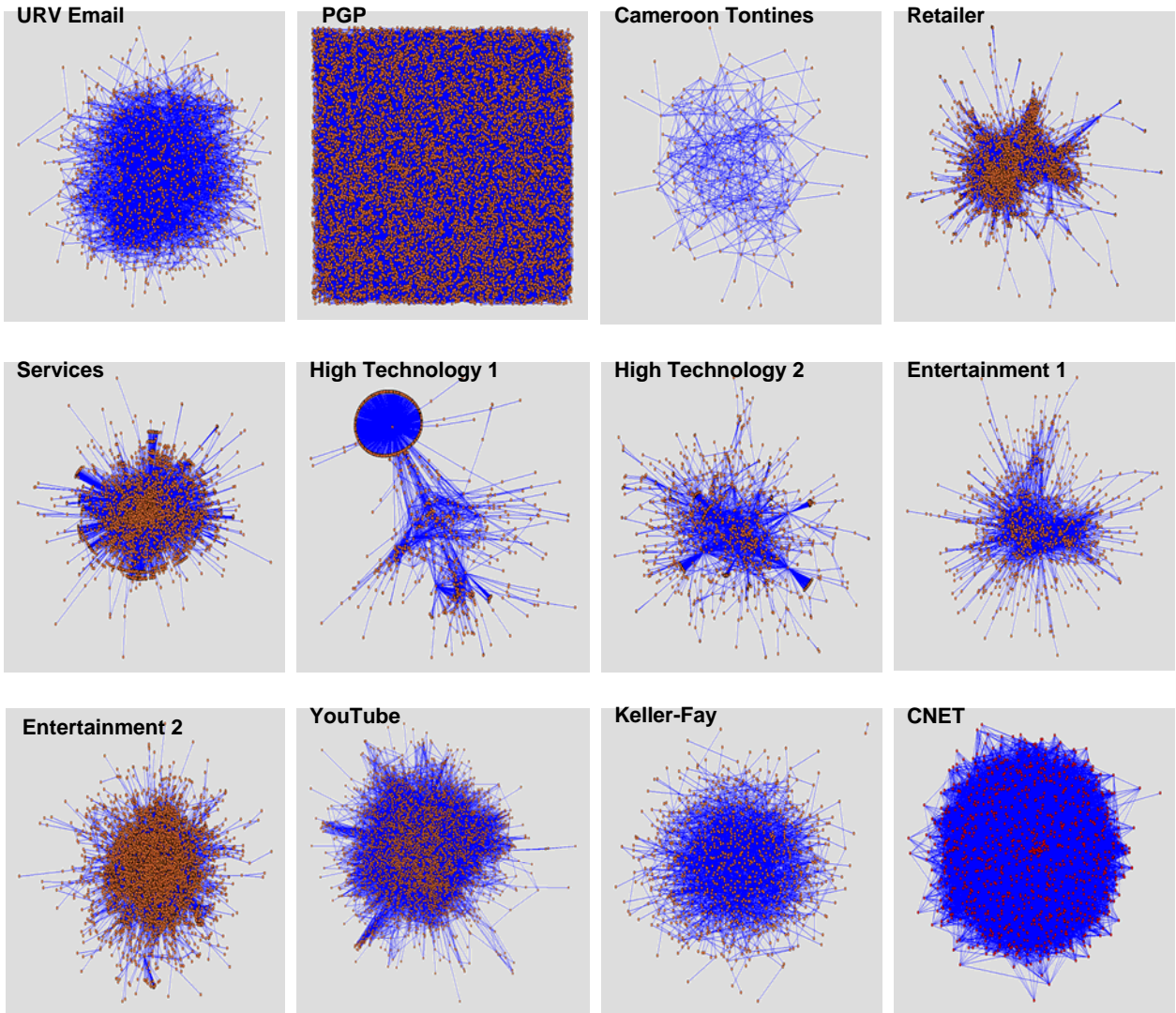
\* Acceleration ratio is the proportion of the total gain in customer equity attributable to acceleration.

**Table 4.** Regression results: Influential–hubs program

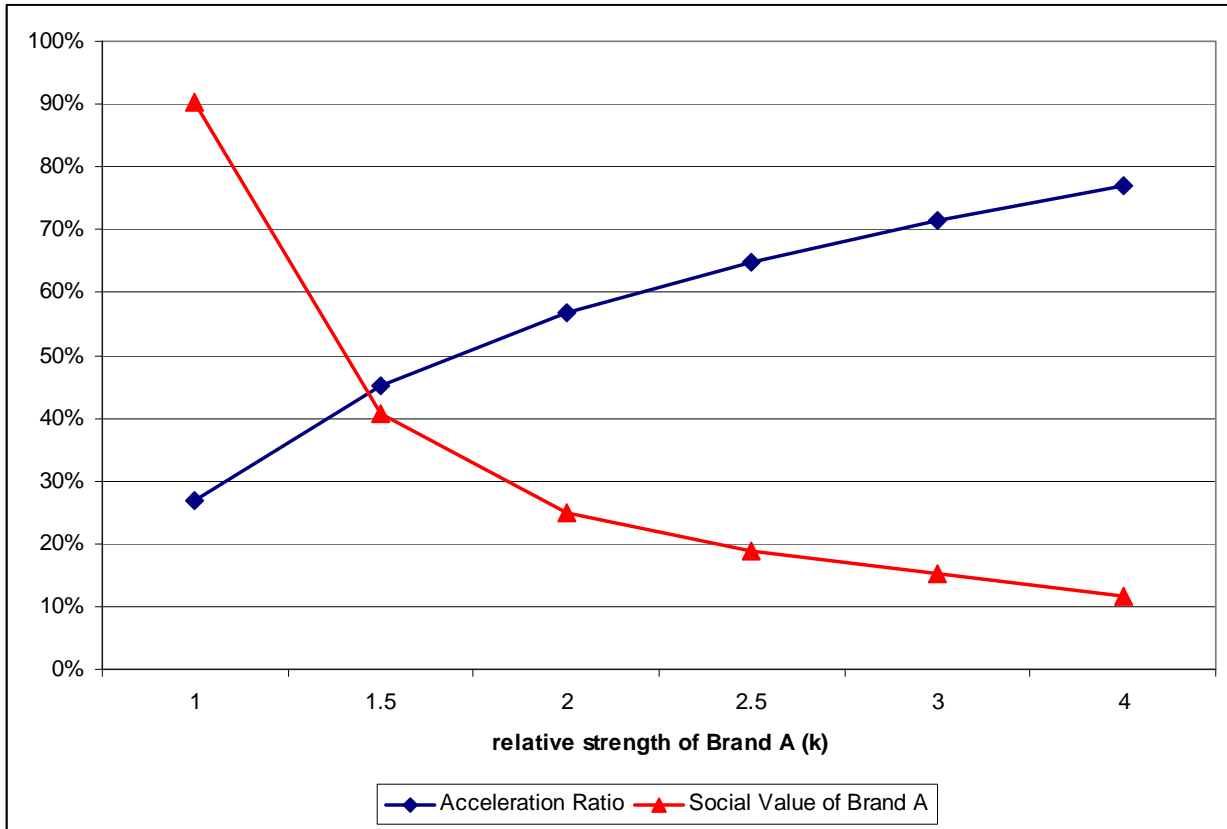
<b>Independent variable</b>	<b>Coefficients</b>	<b>Standard Error</b>
Network size	-0.00002	0.0000005
Average degree	-0.0048	0.00013
Clustering coefficient	-0.561	0.0101
Discount rate	0.0165	0.0027
Number of periods	-0.089	0.0027
Seeding size	-3.457	0.078
Attrition rate	-0.127	0.0027
Relative strength of focal brand	0.236	0.00269
Adjusted R-Square	71.7%	

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

**Figure 1.** Networks graphs

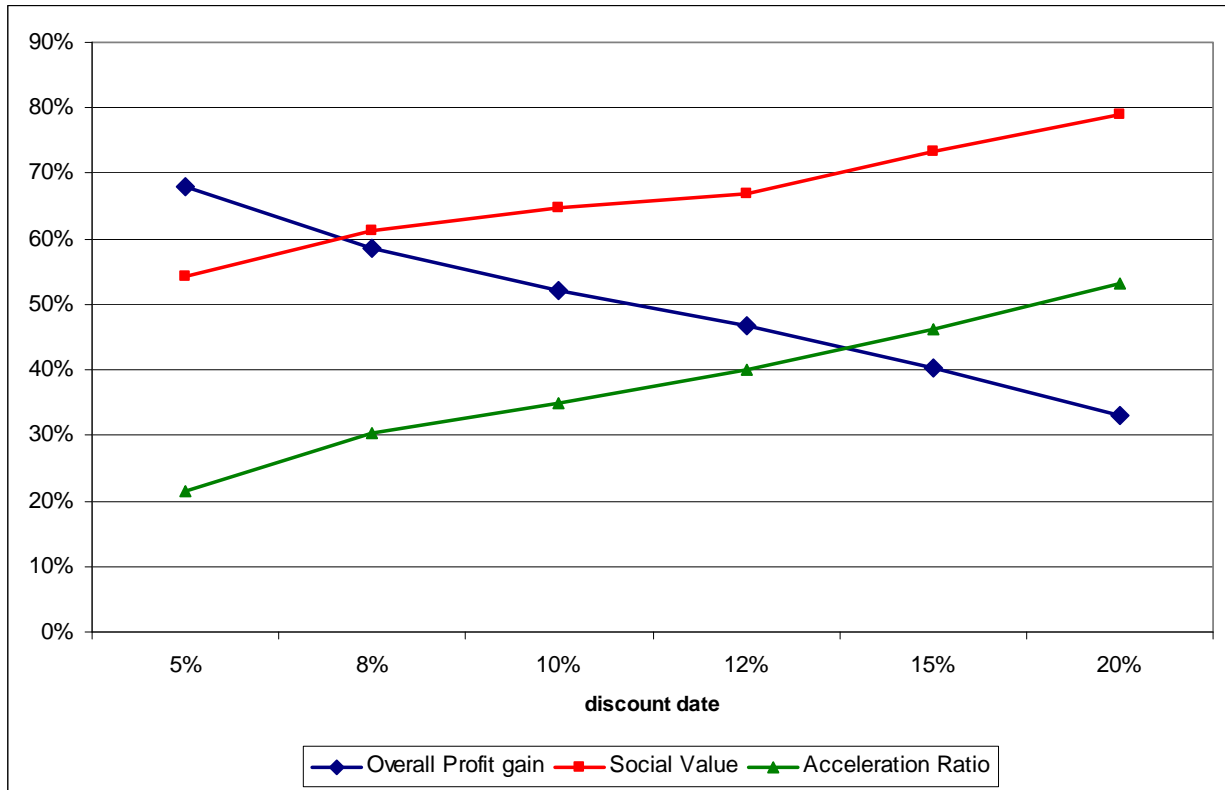


**Figure 2.** Customer acceleration ratio and social value with varying relative brand strength, for a brand operating an influential–experts seeding program; Entertainment 1 Lithium network



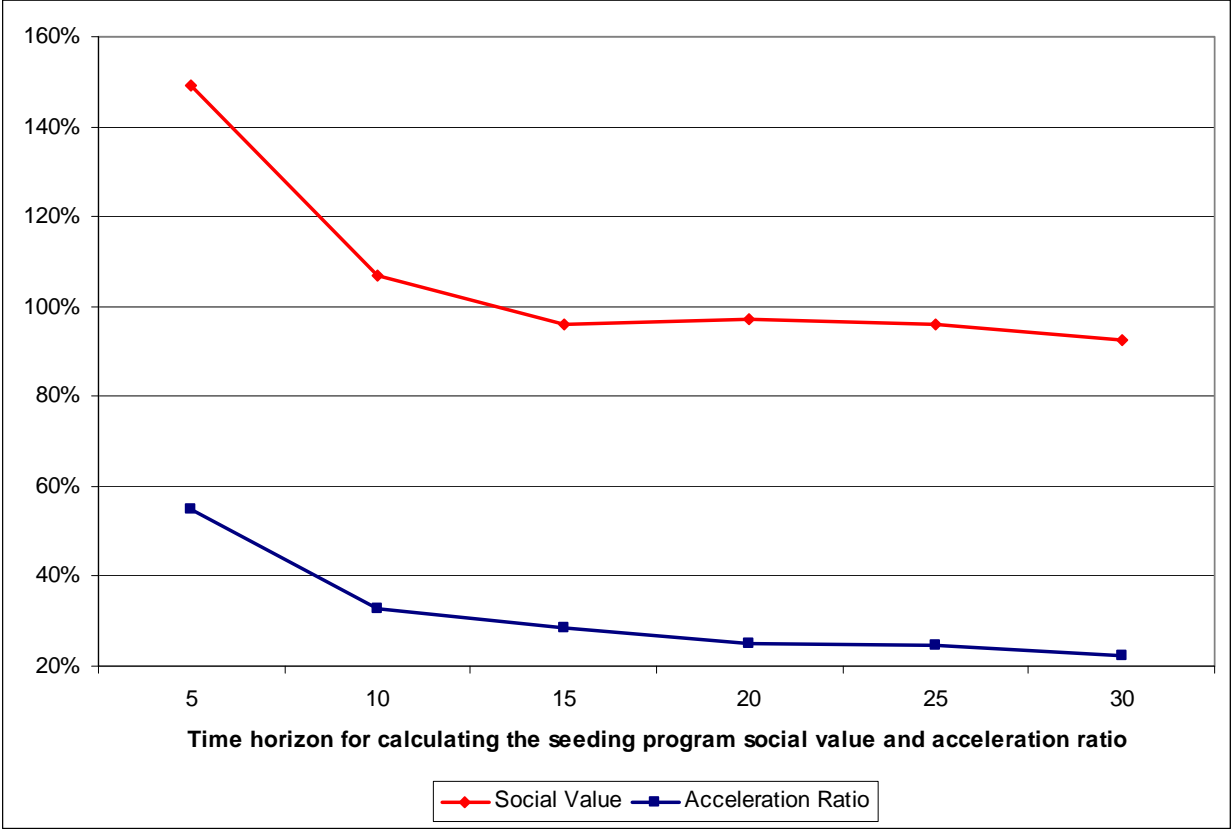


**Figure 3.** The effect of decline in profit per customer on acceleration rate and profitability\*



\* Various levels of discount are used to manipulate profit decline, where the results describe the relative profitability compared to a 0% discount rate. 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.

**Figure 4.** 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



**Figure 5.** 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

