



Marketing Science Institute Working Paper Series 2010
Report No. 10-103

Sources of Social Value in Word-of-mouth Programs

Barak Libai, Eitan Muller, and Renana Peres

"Sources of Social Value in Word-of-Mouth Programs" © 2010 Barak Libai, Eitan Muller, and Renana Peres; Report Summary © 2010 Marketing Science Institute

MSI working papers are distributed for the benefit of MSI corporate and academic members and the general public. Reports are not to be reproduced or published, in any form or by any means, electronic or mechanical, without written permission.

Report Summary

Today, many new product launch campaigns include word-of-mouth “seeding” programs, where marketers target selected customers for product give-aways or discounts in the hope that they will spread the word about the new product to other potential customers. While managers intuitively understand the importance of such programs, they face difficulties when trying to quantify their effects and monetary value to firms.

In this report, authors Libai, Muller, and Peres study the process by which word-of-mouth-related marketing programs for new products create profitability. They define the *social value* of a word-of-mouth program as the global change, over the entire social system, in customer equity that can be attributed to the word-of-mouth program participants. In a competitive market, social value can be created in two main ways: One is by helping the firm to acquire new customers who would not otherwise have bought the product (*acquisition*); and the other is accelerating the purchases of customers who would have purchased anyway (*acceleration*).

Using an agent-based modeling approach, they simulate the penetration process of a new product into a social network of customers. The authors check the growth of the new product on 12 social network structures, taken from real-life applications. Two characteristics are varied in the seeding program: the number of customers targeted for seeding (from .5% to 5% of the potential market), and the types of members targeted (“influentials,” who have a high number of network connections, or “random” customers).

In a market composed of two similar brands, the authors consider scenarios where neither brand has a seeding program, where both have a program, and where only one brand has a program. They also examine the monopoly scenario—when there is only a single brand in the market, and scenarios where one competitor has a stronger brand.

Findings

Seeding programs can create considerable social value. This value is considerably higher when the firm faces a competitor than when it has a brand monopoly. For a firm with no competitor brands that launched a seeding program, the average social value gains in the networks were 17% for random seeding and 27% for influential seeding. All the gains came from acceleration in new product purchases.

When two brands competed in the market, the gains for the brand with a word-of-mouth program were 80% (for random seeding) and 107% (for influential seeding). About two-thirds of these gains were attributable to the acquisition of new customers. In addition, a stronger brand benefits less than a weaker brand from the social value created by the program, and more of its gain is driven by purchase acceleration.

Even disregarding the cost of seeding programs, increasing their size beyond a certain proportion of the market (20%), is not beneficial, as social value reaches a peak and declines.

Finally, while most of the social value created by a seeding program can be achieved using random participants, targeting influentials increased social value by one-third on average. Overall, for influential seeding programs, a higher portion of the social value gain is driven by gains in acceleration.

Conclusion

In addition to offering empirical evidence of the monetary value of seeding programs, this study offers a promising approach to adapting agent-based models to specific empirical networks. For example, firms can use their customer connection data to build an agent-based model focusing on their market reality. Using approaches similar to those used in the study, they can explore the social value of their word-of-mouth marketing campaigns. Given the increasing availability of customer interaction data, this approach may become a practical option for many firms.

Barak Libai is Professor, Faculty of Management, Recanati Graduate School of Business Administration, Tel Aviv University. Eitan Muller is Professor of Marketing, Stern School of Business, New York University, and the Nathan Galston Professor of High-Tech Marketing, Recanati Graduate School of Business Administration, Tel Aviv University. Renana Peres is Visiting Professor, The Wharton School of Business, University of Pennsylvania, and an Assistant Professor of Marketing, Hebrew University of Jerusalem.

Acknowledgments

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, their support, and helpful advice throughout this project. Pete Fader, David Godes, and Raghuram Iyengar contributed additional 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 the Hebrew University of Jerusalem, and the Israel Science Foundation.

Introduction

Consider the following marketing campaigns:

- In 2006, Philips gave away power toothbrushes (Sonicare Essence) to 33,000 North American consumers. Each consumer also received five \$10 rebates to give to others. Philips estimated the campaign to have reached about a million and a half potential customers in North America (Rosen 2009).
- Preceding the launch of Windows 95, Microsoft gave away copies of the software to 450,000 US opinion-leading PC users, or an estimated 5% of the market potential. The record-breaking speed of this software's sales in the post-launch period was largely attributed to this giveaway (Marsden 2006).
- In 2006, Nokia gave away 90 new camera phones (Nokia 6682) to young adults, resulting in 90% of these people posting at least one photo taken using the Nokia handset, and 83% indicating they would recommend it to others (Summerfield 2007).
- In 2008 Hewlett-Packard (HP) provided 31 leading US bloggers each with its new Dragon HDX laptop and asked them to create online contests in which the Dragon was the prize. According to HP, the results of their 31 Days of the Dragon campaign were exceptional: In addition to large-scale online searches for the Dragon, an immediate 85% bump in Dragon sales and a 15% increase in traffic to its HP.com site (Quinton 2008).
- Ford Motor Co. is giving away 100 cars to bloggers, hoping they'll help introduce its new Fiesta, which is set to reach US dealers in early 2010. The idea is "...to get the model's

target audience to drive, and hopefully chatter about the car for months to come” (Tegler 2009).

The above are examples of marketers’ increasing efforts to spread the word via tools such as word-of-mouth agents campaigns (Godes and Mayzlin 2009); programs to identify and impact influencers (Kiss and Bichler 2008); online communities (Valck, van Bruggen, and Wierenga 2009); and viral marketing campaigns (De Bruyn and Lilien 2008). Industry leaders agree that a key challenge for the success of this innovative type of marketing is to achieve financial justification for such campaigns (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). While there is initial evidence as to the contribution of such programs (Godes and Mayzlin 2009; Kumar, Petersen, and Leone 2007; Toubia, Stefen, and Freud 2009), we lack understanding as to the manner in which word of mouth programs create monetary value to the firm.

To appreciate the non-trivial nature of the analysis, consider the fundamental way in which the word of mouth of a new Fiesta adopter (aptly called Henry) can create value for Ford. A common practice engaged in by firms (e.g., Satmetrix 2008) as well as academics (Hogan, Lemon, and Libai 2004; Kumar, Petersen, and Leone 2007) is to sum up the profitability of all the customers referred by Henry and add them to his regular lifetime value as the “word of mouth value” or “referral value” of Henry. As per these methods, Henry's contribution is in *acquisition* of new customers – without him, they would not purchase a Fiesta. However, besides acquisition Henry's contribution comes also in the form of *acceleration* of the adoption of customers who even in his absence would have purchased a Fiesta, but later. Because of the time value of money, Ford can enjoy earlier the profits from these customers.

There is lack of research in the marketing literature on the way in which acceleration and acquisition combine to create value, and their relative portion within this process. Such knowledge is essential for the planning and design of such programs. An informed analysis of the quantity of Fiestas that Ford may want to give away to spread the word, as well as the kind of individuals to whom the Fiesta is given, demands the ability to understand how a word of mouth program translates to monetary value, and how this process is affected by the program's features. Taking into account the whole process can also help to avoid measure biases. For example, Henry's referrals were possibly influenced by other adopters, thus their contribution should be split between all the influencers; The overall contribution can be overestimated since the lifetime value of the referrals is counted twice - once as their direct contributions, and once again as a part of Henry's word-of-mouth value.

Here we study the process by which word of mouth related marketing programs for new products create profitability, providing insights on how customer acquisition and acceleration combine to create value in a competitive scenario. To do so, we define a metric of *customer social value* that measures the financial contribution of a group of customers due to social effects. The premise is that to measure customer social value, one needs to take into account effects across the entire social system: Product-related communication by a customer may kick off a chain reaction that can impact the consumption pattern of others who are further away in terms of network distance or time of adoption, eventually affecting customer equity.

Our exploration of social value is consistent with recent calls for marketers to better their understanding of the social aspects of customer profitability (Gupta et al. 2006; Rust and Chung 2006). While there have been a few pioneering efforts to offer customer profitability measures that explicitly take into account social effects (Kumar, Petersen, and Leone 2007, 2009; Hogan,

Lemon, and Libai 2003, 2004), these efforts are still limited. Notable limitations are that they do not take into account the social system dynamics, the move from individual to group social value, and the role of competition. As we demonstrate, these are critical elements in exploring how acquisition and acceleration combine to create social value.

To translate customers' social system impact into monetary terms, we use an *agent-based model*. In recent years, marketing researchers have increasingly turned to agent-based model simulations to help them untangle the complexity involved in marketing phenomena (Garber et al. 2004; Gilbert et al. 2007; Shaikh, Rangaswamy, and Balakrishnan 2006). Previous marketing work on agent-based models has largely assumed a pre-determined network form, and mostly used a single type of social network to build the simulated market. Here we use data on 12 social network structures: Ten networks whose structure (nodes and edges) is replicated in the simulations, coming from customer brand communities, Internet social networking, and previously published social networks; and two random social networks built based on empirical distributions of social connections. Via the agent-based model, we examine how a hypothetical new product would grow and produce customer equity in each network structure, thereby enabling us to capture a variety of scenarios where customer social value can be created. This process can also serve to demonstrate that firms can use their customer connection data to build a specific agent-based model focusing on their market reality.

We analyze a situation that is common in the use of word of mouth programs and consistent with the above examples: A new product is introduced into a competitive market, and managers consider using a program in which an initial group of customers (which we label here the *seed*) receives the product early on so their word of mouth begins to drive sales. Any surplus process created by this program is in fact the social value of that seeding. We will look into the

measurement of the social value of the seed, how the social value is driven by customer acquisition and acceleration, and how it changes under various market scenarios. We label the percentage of the social value that the firm gains and that can be attributed to adoption acceleration (rather than acquisition) as the *acceleration ratio* of this program. For simplicity, we initially focus on a market composed of two similar brands — and consider a case where neither has a program, both have a program, and only a single brand has a program. We also further examine a case where one competitor has a stronger brand.

Our main results include the following:

- Seeding programs can create considerable social value. The social value of such programs, as well as the acquisition/acceleration dynamics, are largely influenced by the presence of competition in the market. In the networks we examined, for a program initiated by a single brand (a single-brand program), the social value in the presence of competition is about four times that of its social value in a monopoly.
- For a single-brand program, the stronger a given brand is in relation to its competitor, the lower the social value of a word-of-mouth program operated by that brand, and the more this value is driven by acceleration. Hence a stronger brand benefits less than a weaker brand from the social value created by a word-of-mouth program.
- Social value of seeding programs is sub-additive in terms of the number of program members: In common business practice, total program value is determined by summing up the value of all program members' referrals, resulting in a linear return on program size. In contrast, we show that increasing the number of program members creates a diminishing return to social value, which can even decline beyond certain size levels.
- Regarding the choice of program members, we examined both *random seeding programs*, in which program participants were chosen randomly from within a network, and *influential seeding programs*, in which the participants were chosen from the units with the highest number of social ties. We found that while most of the social value created by a seeding program could be achieved using a random program, targeting influentials increased social value by about a third on average in the cases we examined. For influential seeding programs, a higher portion of the social value gain came from acceleration, and the decrease in marginal value with size was faster than for random programs.

The rest of the paper continues as follows. First we discuss mechanisms through which word of mouth generates value, and we define the concept of the social value of a single customer or of a group of customers. Then we present the agent-based model setting in which we examine word-of-mouth programs, as well as the network structure data we use as input to the simulation. We move on to consider various scenarios in terms of competitive activities and market parameters, and conclude with a discussion and consideration of limitations.

How Word of Mouth Creates Value

While word of mouth is widely accepted as an important driver of profits, documenting its effect on profitability is not straightforward; this is largely a result of the complex manner in which social interactions combine to create market-level effects (Godes et al. 2005). Recently, however, marketing researchers have gained access to better data and methods, enabling closer examination of the effectiveness of word of mouth. 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 in online networking sites (Trusov, Bucklin, and Pauwels 2009), and the profitability of new customers (Villanueva, Yoo, and Hanssens 2008).

It remains a key challenge to understand the explicit process by which word of mouth translates to the bottom line. In a competitive market for a new product, word of mouth can create value through two basic mechanisms: acquisition and acceleration.

Customer acquisition refers to the contribution of a customer generated by encouraging the adoption of another customer, who, without the word of mouth would not have adopted, or would

have adopted a competing brand. Literature so far focused on acquisition - the common practice often considers only first-degree acquisition, that is, they measure the contribution of a customer as the sum of the profits obtained from all new customers that he or she directly assisted in acquiring (Satmetrix 2008). However, the influence of a customer may go deeper into the social network. People directly affected by a given customer can further influence others, in turn generating more customer acquisition in a contagion effect. Hogan, Lemon, and Libai (2004) extended the basic measure by taking into account the “full ripple” that reaches customers at higher degrees of separation. They demonstrated a simple way to perform such a measurement and used a straightforward method to integrate this value into the basic customer lifetime value formula.

Kumar, Petersen, and Leone (2007) also investigated customer acquisition, integrating word of mouth into the basic lifetime value formula to measure “referral value” in the context of a referral reward program. They distinguished between two types of acquired customers: For those who would not have purchased without the word of mouth, the full lifetime value of purchases is added to the lifetime value of the original customer. For those who would have purchased the product without the referral, only the saving in customer acquisition costs is added. Using this method, they showed that in a referral reward program, customers who have the highest lifetime value due to their own purchases are not necessarily those who have the highest referral value. In a later study, they further demonstrated how to measure the referral value of customers in a referral reward program for financial services (Kumar, Petersen, and Leone 2009).

Customer acceleration refers to the contribution of a customer who accelerates another customer’s adoption of a product; in this case, one assumes that in the absence of word of mouth, the latter customer would still have adopted the new product, but at a later date. Consistent with

the prominence of marketing as an accelerator of cash streams (Srivastava, Shervani, and Fahey 1998), Hogan, Lemon, and Libai (2003) suggested that in the context of a new product's category-level diffusion, the word-of-mouth value of a customer stems from how she helps to accelerate growth. Using a diffusion model, they demonstrated that the loss of a customer slightly attenuates the adoption process, an attenuation that can translate to a substantial loss that can be considered the "indirect value" of that person.

Note, that in addition to acquisition and acceleration, one could also argue that word-of-mouth can contribute by expanding the category market potential to new population segments, who, without the word of mouth, would have never adopted any of the competing brands. Although such a contribution can exist in real markets, it requires assuming heterogeneity among customers in the propensity to adopt, which is beyond the scope of this paper. We thus follow the mainstream diffusion-of-innovations approach and assume that in any case the entire market will eventually adopt the category.

In a monopolistic diffusion process, wherein the product is eventually adopted by the entire market potential, acceleration is the chief mechanism for creating word-of-mouth value. In competitive markets, however, it is reasonable to expect that both customer acquisition and customer acceleration will combine to drive profitability, possibly in a rather complex manner. If a customer has accelerated a friend's adoption of a product, this can help to either accelerate adoption by others or create customer acquisition, and may continue to affect acquisition and acceleration through the social system. This process may depend on various factors, including the structure of the social system, the speed at which information is transferred regarding the specific product, and the competitive environment. Next, we next present an approach that aims to incorporate all these influences and explore the acceleration/acquisition dynamics.

The Social Value of an Individual and a Word-of-mouth Program

In the 1946 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 if he had never existed. The notion is that only in the absence of someone can we really understand his or her value. Here we suggest a similar notion for assessing the social value of customers. 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 selling firm will end up with a certain level of customer equity. This constitutes a scenario of “life without that customer’s word of mouth”. Now consider a scenario that is identical to the previous one, except that in this case this individual generates word of mouth about the brand. This local change creates a “shock” to the social system and therefore has implications on 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 than they would in the alternative scenario, and some who would not otherwise have purchased the product may adopt it. These effects will translate into a change in customer equity due to both acceleration and customer acquisition. The only difference between the two scenarios is the presence of word-of-mouth by an individual customer; thus, we define the difference in customer equity between the two scenarios as the social value of this individual.

Similarly, we can apply this notion to the social value created by a word-of-mouth program. A prominent type of word-of-mouth program is a “seeding program”, in which the product is presented (given or sold) to an initial seed of customers, in the hope that their adoption will begin a contagion process. Various types of programs can serve as seeding programs, including word-of-mouth agent programs (Godes and Mayzlin 2009), opinion leader programs (Dunn 2007), and

brand-related communities (Thompson and Sinha 2008). The social value of a seeding group should be calculated by assessing, on the social-system level, the monetary results achieved when the seeding group adopts a product early on, and then comparing those results with those achieved in the absence of the seeding program.

Because of the important role of word of mouth in the diffusion of innovations, and following much of the literature that has focused on word-of-mouth effects in the context of new products, we focus on the customer equity created when a social system adopts a new product. 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 of value or a repeat-purchase product whose value is the estimated lifetime value. Looking at the profitability of a group of g customers out of the overall N customers, we consider the following types of profitability:

- **Direct value** $V_{direct}(g)$: the profitability to the firm that stems from the purchases of the g customers.
- **Social Value** $V_{social}(g)$: the profitability to the firm that stems from the effect of the g customers on the other $(N-g)$ customers.
- **Total value** $V_{total}(g)$: The sum of both: $V_{total}(g) = V_{direct}(g) + V_{indirect}(g)$

Consider a group of g customers subjected to a program under which group members adopt the product at launch instead of at future times, with a tilde (\sim) denoting values obtained in this scenario. The extra value of the program (denoted $\tilde{V}_{program}$) is the difference in customer equity between the scenario that includes the program and the scenario that does not include the

program. (Note that at this point we are not considering the cost of the program, only the extra value it creates.) Thus, $\tilde{V}_{program} = \tilde{V}_{total}(T) - V_{total}(T)$. The program value stems from two sources:

- The early adoption of the g customers creates value because of the time value of money. If initially the direct value of the g customers was $V_{direct}(g)$, now it is the sum of the lifetime values of these customers at time zero, denoted by $\tilde{V}_{direct}(g)$. Therefore the direct value of the program is $\tilde{V}_{program_direct}(g) = \tilde{V}_{direct}(g) - V_{direct}(g)$.
- We determine the social value of the program $\tilde{V}_{program_social}(g)$ according to how the program affects the influence of the g customers on others. This is our focus. From the above it follows that the social value of the program is its total value minus the direct value of the program, and therefore the social value of a program is given in Equation 1:

$$\begin{aligned}\tilde{V}_{program_social}(g) &= \tilde{V}_{total}(N) - V_{total}(N) - \tilde{V}_{program_direct}(g) = \\ &= V_{total}(N) - V_{total}(N) - \tilde{V}_{direct}(g) + V_{direct}(g)\end{aligned}$$

(1)

Note that the overall profit from the program will of course be lower if products are given away or sold at a deep discount to encourage participation. This factor would be taken into account in the cost calculation rather than in the value equation presented here.

An Agent-based Model of a Word-of-mouth Program

We next examine how acquisition and acceleration combine to create social value for a word-of-mouth program. To do so, we use empirically based 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 2002). Agent-based models are used to simulate events and aggregate outcomes in a would-be-world, in which relationships at the individual level are similar to those observed in the real world. These models are used in the social sciences to model social processes such as diffusion, collective action, and group influence (Macy and Willer 2002), as well as economic activity in general (Tsfatsion 2003). Agent-based models are also increasingly being used in the marketing literature, particularly to examine issues related to new product growth (Delre et al. 2007; Garber et al. 2004; Shaikh, Rangaswamy, and Balakrishnan 2006). The agent-based model used here describes a social system of customers who adopt a brand of a new product in a competitive setting. Our aim is to follow the profitability of each brand under various scenarios. To do so, we first need to decide on the structure of this social system and on the rules that govern the individual adoption decision and the profitability that stems from it. We present these basic features in the following subsections.

The social network structure

The classic version of cellular automata depicts the market as a matrix of cells, in which each cell represents an individual consumer. Each cell is able to receive information from the adjacent surrounding cells and to make decisions at each iteration of the simulation (representing consecutive periods of time). While this classical version had been shown to capture a range of social phenomena effectively (Sarkar 2000), researchers also aim to use more realistic representations of the market, for example examining social networks of various sizes and connections between agents (Goldenberg, Libai, and Muller 2001).

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 case of a single network. Here, we examine the social value of seeding programs using empirical connectivity data on the 12 networks presented in Table 1. With the exception of the last two networks, all the networks we examined are exact replicas of real network nodes and ties.

Papers on three of the social networks (networks 1–3) have been published, and their data were graciously contributed to us by the authors. These networks include an email connection network in URV university in Spain (Guimera et al. 2003), the main (giant) 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, who were asked about their social communications as part of a study on the use of contraceptives (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 in four different fields: 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. The social networks presented here include members who surpassed a minimal level of involvement in the community, as defined by Lithium¹.

Network 10 was obtained from YouTube.com. YouTube is widely known as a media site, but a less well-known fact is, that it also operates a social network for users who upload videos. The social network we present here was created using a “snowball technique”. We first collected data on the users who uploaded the 25 most viewed videos in June 2009. We expanded our sample

network by adding each YouTube user who was linked in a “friendship” connection to a member of our network and had at least two additional “friendship” connections with other users within the general YouTube social network. The final data set included more than 4,000 users.

The data for networks 1–10 fully represent the connections among members; that is, the data 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 only had the degree distribution (that is, the distribution of the number of connections in the population). Therefore, we constructed a randomly assigned social network of 1000 units based on a reported degree distribution. Network 11 uses a distribution based on the *TalkTrack* by the Keller Fay group (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 connections of more than 11,000 customers who visited the CNET site and responded to a survey on social networks (Smith et al. 2007). The degree distribution is based on participants’ responses to the survey, in which they stated how many people they communicated with at least once a month either online or offline. Note that we use these networks only as examples for real-life connectivity structures and do not relate to any other specific aspect of these networks.

For each network structure, Table 1 presents the key network parameters, usually 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 people in direct contact, for both the entire population as well as 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). In Table 1 we observe considerable variation in parameter values among networks; this demonstrates the diversity of the networks on which we perform the simulations. The graphs of the networks can be found at <http://socialequity.homestead.com>. Note that all the networks presented here have a single major component, that is, there are almost no 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 compete for the potential adopters: brand A and brand B. Each cell can accept one of three activation states: “0”, representing a potential customer who has not adopted the innovative product; “A”, representing a customer who adopted brand A; and “B” for an adopters of brand B. In addition, irreversibility of transition is assumed, so that consumers cannot un-adopt after they have adopted. In accordance with classical diffusion modeling, the transition from potential adopter to adopter depends on two factors: *External influence*, represented by the probability δ that an individual will be influenced by sales force, 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 individual from the same social network who has already adopted the brand. The simulation is run for 30 consecutive time periods (iterations), and the adoption propagates in the system according to the adoption rule described below.

Our focus here is on the fundamental dynamics of customer social value, and so our aim is to keep the adoption dynamics as simple as possible. Thus, beyond the empirically based network

structure and the effect of external and internal influence, we try not to make additional restricting assumptions or add parameters. This is in contrast to some of the agent-based literature that has taken advantage of the flexibility of this tool to study more complex network adoption features such as the differential effects of weak and strong ties, negative versus positive word of mouth, and non-linear advertising effects (e.g., Goldenberg et al. 2007).

The appendix describes the algorithm we use to generate the adoption probability given external and internal effects in the market. Note that regarding the competitive environment, we begin by looking at similar brands. This translates to identical external and internal parameters for the two brands, which allows us to focus on the effect of the word-of-mouth program and not that of competitive strength. Later, however, we also consider the case of differential brand strength. We also assume homogeneity among units in terms of δ and q ; when we ran simulations allowing for heterogeneity in these parameters, results remained consistent.

Customer Equity

In each of the scenarios presented below, we measure the customer equity for each brand, which is the sum of the discounted cash flow from all adopters over 30 time periods. We assume that each adopter contributes a normalized value of 1 monetary unit (to which we refer here as \$). 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.

Our focus is on the interaction between acquisition, that is, the acquisition of customers who might have not purchased the brand without the word of mouth, and acceleration, whose monetary value is attributed to the time value of money. With a zero discount rate, most of the value generated should result from acquisition, although acceleration might also indirectly affect

social value, for example if a customer who accelerates her purchase helps to bring in a customer who might have gone to a competing brand. Since the influence of discount rate on the amount generated from acceleration is expected to be monotonic, and consistent with much of the agent-based profitability simulations, we use a discount rate of 10% per time period (e.g., Goldenberg, Libai, and Muller 2001).

When a seed of customers adopts earlier, customer equity increases not only due to social value, but also due to the direct monetary value derived from the early adoption of the seeding group itself as explained in Equation 1. In the following analysis, the customer equity gain we report is that deriving from the social effect only, controlling for the time-based value of early adoptions on the part of the seed itself.

The word-of-mouth program

As described above, we use a word-of-mouth seeding program in which a selected group of individuals (a seed) initiates the diffusion process in the network. In the simulation, we operationalize the word-of-mouth program by assigning the program members with a nonzero initial activation, A or B, depending on the brand (or brands) offering the program.

We vary two key characteristics for the seeding program: number of members (size) and types of members. Following discussions with managers and observation of industry practice, we varied the program size from 0.5% to 5% of the potential market. The second issue is whom to target as program members. Influentials (also labeled *influencers*, *opinion leaders*, and *hubs*) — or individuals who have a strong effect on the flow of information in the network — have attracted marketers' attention for quite a while (Goldenberg et al. 2009; Iyengar, Van den Bulte, and Valente 2008; Keller and Berry 2003; Nair, Manchanda, and Bhatia 2008). Marketers have developed methods of identifying such individuals and attracting them to word-of-mouth

programs (Dunn 2007). The alternative is to seed the market with random customers, an option recently advocated by some (Watts 2007). We consider both these options, termed *influential seeding* and *random seeding*, respectively. For random seeding, we formed a group of randomly selected customers who would adopt the brand at time zero. For influential seeding, consistent with previous research, for each network, we randomly chose the seed members from the 10% of the individuals with the highest number of connections (Watts and Dodds 2007). 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 both types of seeding. The parameter range we used is presented in Table 2.

The Program's Effect on Customer Equity: Results

For each of the 12 networks, we ran simulations of the diffusion of a hypothetical new product. For each network, we varied all the parameters in a full factorial design, measuring the customer equity, and assessing the social value obtained in each simulation. We compared five types of scenarios:

1. No seeding program
2. Brand A operates a random seeding program
3. Both brands (A and B) operate random seeding programs
4. Brand A operates an influential seeding program
5. Both brands (A and B) operate influential seeding programs

Since we were interested in measuring the differences in customer equity between scenarios, we operated in each run the five scenarios using the same series of randomly drawn numbers to realize individual adoption probabilities. Thus, the only differences are attributed to the changes in the program rather to random fluctuation. To avoid stochastic effects of a single run, each combination of parameters in each network was run 20 times, with different realizations. For

each network and for each scenario, we report the average results across all runs and parameter values.

Table 4 summarizes the main results for the 12 networks. Unless otherwise specified, each value reported below constitutes an average of the values obtained at the end of the 30 periods, across all runs of the corresponding scenario (across all values for the external and internal influences and the size of the seed). To help demonstrate how we arrived at the results in Table 4, Table 3 presents detailed results for the Keller Fay network (Network 11).

As shown in the example in Table 3 (column 1), if brand A starts a random seeding program, its average equity increases from equity of 222.3 (in the no seeding program) to 368.8, a gain of 65.9% (indicated in row 2, column 4). Following our definition of social value, this difference of 146.5 constitutes the social value of the group of customers who formed the seed. If brand B uses a seeding program as well, the customer equity for each brand is about 260, a gain of 16.7% for each brand compared to the no-program case. The parallel results for influential seeding programs are higher: brand A gains 97.5% if it operates a program alone, and 26.7% if both brands operate a program. Columns 1–4 of Table 4 present the percentages in equity gain (equivalent to column 4 in Table 3) for each of the 12 networks, derived through the same calculations used in the example (Table 3).

Column 5 of Table 4 shows the proportion of the total gain that is attributable to customer acceleration (termed here “acceleration ratio”) in a brand A-only random seeding program. We count as acceleration all cases in which an adopter adopted the same brand either with or without the seeding program, but with the program adopted the brand earlier. Acquisition is counted as any case of an adopter who, without the program, adopted the competitor's brand (or did not adopt at all), and with the program, adopted the focal brand, *regardless* of the timing of this

adoption. Theoretically, due to random fluctuations, there could be also an option for attenuation (customers who adopted later with the program than without the program), but since we ran the five scenarios with the same random realization, there are no attenuation cases in our simulation results. The agent based simulation enables us to track the individual adoptions in each scenario and to count the number of acquisitions and their monetary value. To simplify the explanation, we illustrate the values through the following aggregate equity numbers: In the Keller Fay example in Table 3, when only brand A operates a random program, brand A's customer equity increases by \$146.5, whereas brand B's customer equity decreases by \$95.1. Since A gained what B lost, we can conclude that $95.1/146.5 = 64.9\%$ is the percentage gained through customer acquisition, and the remaining 35.1% is the percentage that stems from customer acceleration. Therefore, its acceleration ratio in column 1, row 11 of Table 4 is 35.1%. If Brand A alone was to run an influential seeding program (column 6 of Table 4), brand A would gain \$216.8 more than it would with no program, whereas B would lose \$127.1. Thus, brand A's customer acquisition proportion is 58.6% and, correspondingly the acceleration ratio is 41.4%.

As one might expect, when two brands are similar and both operate a seeding program, their acquisition from each other is symmetric, and all gains are generated by acceleration. Thus, even if there is no change in the relative gain of one brand in comparison with the other, the seeding programs generate a total higher social value from which both brands benefit.

Note that the results in Table 4 are largely consistent across various networks, even though the networks themselves vary greatly in their basic characteristics (Table 1). For example, if we take the ratio of the standard deviation to the mean of each parameter as an indication of variability, the average of this ratio across the four network parameters in Table 1 is 0.76, which is almost four times larger than the average of this ratio for the six columns of Table 4, which is 0.2. This

might be due to the fact that the differences between scenarios are measured within each network, and therefore the network characteristics have a smaller role than the competitive dynamics. As mentioned above, the networks in our dataset are single components, and results might change in networks composed of many isolated units or clusters.

From Table 4 we can derive the following conclusions on the dynamics of social value.

Program competition drives the social value of seeding programs

Looking at Columns 1 and 3 in Table 4, we see that the social value gain when a single competitor operates a seeding program is on average 80.4% for a random seeding program and 107.3% for an influential seeding program. We decided to examine to what extent these gains are driven by the competitive scenario we describe, so we ran a version of the program in which brand A was the sole player in the market. In this case, the average gains across networks were 17% (standard deviation of 4%) for the random seeding program and 27% (4% s.d.) for the influential seeding program. We see that indeed, the value of the program is considerably higher when the firm faces a competitor than when it has a monopoly.

The acceleration ratio dynamics can help to explain how this happens. In the case of a monopoly, all customers will eventually adopt the same brand; therefore, all gains in equity result from acceleration. In a competitive scenario, the seeding program can also add value through acquisition, and as Columns 5 and 6 of Table 4 indicate, this is a major part of the gain. Thus, in a competitive scenario the seeding program creates the joint effect of acquisition and acceleration to generate a higher equity gain.

In the case of a single brand program, is there a midway in terms of the acceleration ratio between the *acceleration*-based monopoly case and the largely *acquisition*-based competitive

scenario? When Brand A runs a program alone and the two brands are equivalent, the social value come from the joint effect of acquisition and acceleration. The stronger brand A is, (in terms of δ and q) in relation to brand B, the more similar brand A becomes to a monopoly. Thus, the proportion of its social value from acquisition declines, the overall social value declines, and all remaining gains comes from acceleration. One can say that the stronger brand A is relative to brand B, the less its need for a seeding program to cope with competition, and the role of the program becomes limited to accelerating the adoption by customers who would have adopted A in any case.

We demonstrate this issue using the Keller Fay data (Network 11). We ran an additional simulation, this time with brand A's δ and q higher than those of brand B, and with a brand A-only random seeding program. The difference in brand strength is operationalized by a parameter k that multiplies the communication parameters q and δ , and therefore represents the relative strength of the brand: If $k = 2$, for example, it means that the δ and q values of brand A are twice those of brand B, and thus brand A is twice as strong in terms of adoption. Hence, $k = 1$ represents the symmetric, largely acquisition-based case, and large values of k represent cases in which brand A resembles a monopoly.

Figure 1 shows gains in customer equity and the acceleration ratio for random programs under various levels of relative strength for brand A. Similar results are obtained for an influential seeding program (not shown in the figure). We observe that increasing the strength of brand A is associated with exponential decline in program gains and an increasing role of customer acceleration in these gains. We observe similar results for the other networks.

We summarize this analysis in the following two results:

Result 1: *The competitive program effect:* Social value and the acceleration ratio are largely driven by competitive influences. For a single brand program, the average social value gains in the networks we examined were 17% for a random seeding program and 27% for an influential seeding program; all these gains came from acceleration. In contrast, in a competitive scenario, the gains for a single-brand program were 80% and 107%, for random and influential seeding programs respectively, and about two-thirds of these gains were attributable to acquisition.

Result 2: *The brand strength effect:* The relative strength of the brand affects both social value gains and the acceleration ratio. With a single brand program, the stronger a brand is relative to the competitor, the lower its program's social value, and the more its gains are driven by acceleration. Hence, the stronger brand benefits less than the weaker brand from the social value created by a word-of-mouth program.

Effect of program size

The results we have presented thus far are an average over the various program sizes presented in Table 2. Since program size is a basic managerial decision variable for word-of-mouth programs, and given the variety of sizes seen in the market, we wanted to see the extent to which this parameter affects social value.

In much of the lifetime value literature, customer equity is computed as the simple linear sum of customer lifetime values. Therefore, in models in which total social value is computed as the sum of the lifetime value of customers who are referred to the brand, it seems that the total social value should show a linear relationship to the number of program members. In practice, however, this may not be the case for two reasons. The first is that when a program size is increased, the additional members may partly act to influence customers who would have adopted even with the smaller program. This is especially true when the additional program members are relatively close (in terms of their position in the network) to previous program members. The second reason, relevant especially to seeding programs, is that of saturation. In an

effect similar to that observed in diffusion models, the more people one moves to the seeding program, the fewer people they can influence. When the numbers become large enough, the effectiveness of the program can be substantially affected. This effect is shown in Figure 2, a graph of equity gains in a brand-A-only program under multiple seed sizes, for the Keller Fay data. We observed similar results for the other networks. To consider the theoretical effect of large size programs, we carried out simulations with seed sizes larger than 5% of the market potential, which was the maximum we considered in previous simulations. In the case of a random program we increased the seed size to up to 100% of the potential market. For influentials we increased the seed size to 10% of the potential market, the maximum given our assumptions regarding the proportion of influentials in the population.

A number of issues are notable here: First, for smaller program sizes, including the range we examined in most of our simulations, the social value created is sub-additive, i.e., the marginal value of each new customer is lower than that of existing customers. This is true for both random and influential seeding programs. However, while influential seeding programs provide higher social value compared with random programs, the decline in the marginal value of influentials is faster than that of random customers.

Second, beyond a certain seed size (about 20% in the Keller Fay case), the social value of a seeding program reaches a peak and declines. Hence, even disregarding any cost in increasing the program size, increasing the size beyond a modest proportion of the market potential is not beneficial. For influentials, while our 10% limit did not enable us to see the decline, we get very close to a peak that happens earlier than for the random program. In the Keller Fay case, the peak

is achieved with an influential seed size of about 10% of the population, compared with 20% for a random program. Thus, we formulate the following results:

Result 3. The social value of seeding programs is sub-additive, and declines once seed size increases beyond a certain point.

Result 4. Compared with a random program, the marginal social value of an influential seeding program decreases faster in relation to program size and reaches its peak under a smaller program size.

Influential versus random seeding programs

One interesting feature of our approach is its ability to examine the dynamics of influential seeding programs. While identifying and getting to influentials is costly, firms invest considerably toward this end (Dunn 2007; Marsden 2006). Yet there have been recent arguments that influentials do not create contagion processes that differ significantly from those of other types of customers (Watts and Dodds 2007), generating further calls for marketers to thus consider the use of such programs and possibly opt for random seeding (Watts 2007). There are also academic findings on the powerful role of random seeding in market entry (Libai, Muller, and Peres 2005). On the other hand, there is a body of evidence from both the industry (Keller and Berry 2003) and academia (Goldenberg et al. 2009; Iyengar, Van den Bulte, and Valente 2008) indicating the role of influentials in product diffusion. What was missing from the discussion to date, however, is the fact that from the firm's point of view, influentials' contributions should ultimately be measured not in conversations, persuasiveness, or even contagion processes, but rather in their monetary effect on customer equity. Our analysis can thus help introduce the monetary effect into the discussion.

Table 4 indicates that of the total value created by an influential seeding program in the networks we analyzed, about 75% on average could be achieved by a random program (in both the single-brand program and two-brand program cases). 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, it can raise the social value by an average of 33% in comparison with a random seeding program.

The shift from random to influential seeding programs also has implications for the acceleration ratio. As can be seen from the last two columns of Table 4, under a single-brand influential program, customer acquisition still constitutes the majority of gain in equity; however, the acceleration rises (by 7% on average). Thus, influentials create more value through acceleration than do random customers.

Result 5: While most of the social value created by a seeding program can be achieved by a random program, targeting influentials can increase social value considerably (by 33% on average in the networks we examined).

Result 6: Under influential seeding programs, the role of acceleration in driving social value is more important than it is under random programs.

Discussion

If we return to the examples of seeding campaigns presented in the introduction, we observe substantial variability in terms of these programs' goals and measures of success. While these goals and measures are certainly worthwhile, in this paper we pursue the bottom-line goal of discounted cash flow to justify a word-of-mouth program. In particular, we distinguish between the two mechanisms through which such a program creates value, i.e., acquisition of customers who without the program would adopt competing brands, and adoption acceleration of those customers who would have bought the new product even in the absence of the program, but at a later time. The main takeaways of our research are as follows:

A network-based measurement of the social value of a customer

Since information spread by a group of individuals creates a shock to the social system, one needs to look at the system-level effects to understand the consequences of that shock. We acknowledge that practically speaking, such insights are difficult to build on, as firms generally seek straightforward measures that can be derived using available data, without engaging in the need to map their social network and run complex simulations. Yet there is still a need to point out the limitations of current approaches and chart a course toward an extended analysis.

One issue is that short-term increases in sales following a word-of-mouth program might cause a firm to overestimate the true effect of the program, as a sizeable portion of these sales might simply be accelerated sales. Hence caution should be used in interpreting increases in sales following a word-of-mouth program. While we provide indications in this study as to the percentage of acceleration that could be expected under various market conditions, clearly more comprehensive empirical analysis is needed for practical applications.

Another issue is the effect of program size on social value. While past research has focused on the individual level, marketers' interest will often be in the group-level value. This shift is non-trivial because aggregation of individual social values is not linear. Firms use a variety of volumes in seeding programs, with a proportion of 1% of the market potential sometimes mentioned as a rule of thumb for the size of the seed (Marsden 2006; Rosen 2009); however, this figure is not based on rigorous analysis. An informed calculation should take into account costs as well as network structure and product characteristics. As we have shown, the social value of seeding programs is sub-additive, that is, the social value of a group is less than the sum of the social value of each of its members, and the dynamics of random and influential seeding program are different. These results should be taken into account in any optimization performed.

Such calculations may demand network-specific analysis. Yet one promising approach demonstrated here is the adaptation of the agent-based model to specific empirical networks. In recent years, consulting firms have begun using agent-based models to help companies plan their strategic market behaviors (North and Macal 2007). If firms can learn the specific structure of their customer networks, then using approaches similar to those used in this study, they can build agent-based models that enable them to explore social value. We believe that given the increasing availability of customer interaction data via various customer communication databases, this option may become a practical one for many in the near future.

The role of competition

We have shown how the dynamics and magnitude of social value can change considerably depending on the competitive scenario and the relative strength of a brand. This issue is of special interest, as much of the literature on word-of-mouth effects has not explicitly considered competition and its impact on word-of-mouth effectiveness (Libai, Muller, and Peres 2009b). Our work elucidates the advantage of preempting a competitor by using a word-of-mouth program, as well as the need to address brand strength when considering the use of a program.

The monetary value of time in social network analysis

Firms increasingly use social network analysis tools to derive managerial implications and marketing-mix strategies that take into account customer connections. An important issue that users of such data should take into account is the need to translate network-level behavior into monetary terms that are of interest to firms. One such term is the value of time. While the role of opinion leaders as accelerators of diffusion has been noted (Valente and Davis 1999), social network analysis has traditionally centered more on patterns of information spread rather than on

how long it takes or how much profit it creates. This role differs in a business environment in which time is money, and acceleration affects profitability.

This precept is evident in the case of influential seeding programs. Thus far, research on the role of influentials in social networking has not emphasized monetary measures, as it has primarily come from disciplines such as sociology, communications, and political science, which do not focus on profits, and which do not relate to the temporal aspects of performance (Burt 1999; Valente and Davis 1999; Weimann 1994). Using a financial measure, we saw here both the power of random seeding and the substantial incremental value of influential seeding programs. In practice, many seeding programs targeting influentials — especially Web-based influentials such as leading bloggers (e.g., the aforementioned HP example) — may create high impact (Marsden 2006). Critique of the effectiveness of influentials programs has created an industry debate with counterclaims that point to the success of such programs and their importance for firms (Carl 2007). Our aim here is not to rule on the utility of specific programs, especially as in order to do so, we would have to take into account the cost of identifying and affecting influentials. We do want to stress that the discussion should ultimately focus on the social value of customers.

Future Extensions and Limitations

Given the flexibility of the agent-based model approach, numerous extensions and explorations could potentially be added to our analysis. Above we focused on the fundamental dynamics of social value; below we present several ways this approach can be extended and adapted to better fit specific market realities.

Network characteristics

We covered 12 networks in this study. While our results appear to be robust across various network structures, more social networks of various sources and structures should be examined in future research. For example, consistent with much of the social networks literature, the networks we examined were composed mostly of a single main component. One could also explore networks that are composed of small, unconnected components. In addition, we did not explore the direction of communication among nodes or their strength of ties, and how heterogeneity in communication patterns among customers affects the social value. The increasing availability of network data should make this information available to researchers and serve to fine-tune our results. Given more networks to examine, we will also be better able to explore the relationship between network structure and the creation of social value.

Customer profitability dynamics

Differing customer profitability dynamics can also be examined. While we did not vary the direct customer profitability, in some industries we can find large variations in the lifetime value among customers. An interesting question is how a variance in lifetime value correlates to social value dynamics. For a for a mature market, Kumar, Petersen, and Leone (2009) found that referral reward program customers whose referral value is the highest are not necessarily those with the highest lifetime value, and Godes and Mayzlin (2009) suggest that loyal customers may be less valuable as word-of-mouth agents, since their friends may have already experienced the product. While this may be a function of the specific program type, this relationship is clearly an interesting one to examine in the context of a new product seeding program,

Types of social influences

While we focused here on the social value created by word-of-mouth programs, other types of social influence may have important roles in the contagion processes that characterize the growth of new products (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 compared with word-of-mouth (Goldenberg, Libai, and Muller 2010).

Recently, researchers have begun exploring the indirect value of customers in double-sided markets in which network externalities have an important role (Gupta, Mela, and Vidal-Sanz 2006). This can be further explored using the agent-based model and social value approach.

Normative implications

As our work is descriptive in nature, an interesting next step is to consider normative implications that will help the firm to increase profits. Among these are how much of an investment to make in a program; the optimal degree of subsidy to the seed; and the effects of product pricing. As with other competitive models, given information on costs and benefits, one might inquire as to the optimal competitive strategy when operating word-of-mouth programs.

Conclusion

In a recent review of the customer networks literature, Van den Bulte (2010) pointed to the difficulty of assessing the value of an individual who is a part of a network. It was argued that the complex dynamics of the inter-customer connection make any straightforward analysis difficult to perform and leave researchers far from a satisfactory solution. Indeed, only scant research has begun to confront this issue to date. We believe the approach presented herein can help to untangle this complexity. 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 has been a significant step toward this goal.

Appendix: Adoption Probability

We used a competing risk model (e.g., Goldenberg, Libai, and Muller 2001), where each adopter connected to i can independently try to convince i to adopt. Thus, the adoption probability of i is one minus the probability that all these adopters, as well as the advertising efforts failed the task: $p_i(t) = 1 - (1 - \delta)(1 - q)^{N_i(t)}$, where $N_i(t)$ is the number of adopters in i 's personal social network at time t . Advertising here is considered as an additional independent influence. 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 models that have demonstrated a good fit to empirical data (Libai, Muller, and Peres 2009a, 2009b). Now assume two brands, A and B , each having its own external influence, i.e., δ_A and δ_B , and internal influence q_A and q_B . Adopters of A and B independently try to influence a potential adopter i to adopt their brand. The probability of i being successfully influenced to adopt brand A by at least one adopter of A is given by:

$$p_i^A = 1 - (1 - \delta_A)(1 - q_A)^{N_i^A} \quad (1)$$

Where N_i^A denotes all consumers in i 's personal social network who have adopted brand A . In a monopoly scenario, this equation would suffice to represent adoption probability. However, under competition, brand B adopters could also successfully influence i to adopt their brand. Therefore,

$$p_i^B = 1 - (1 - \delta_B)(1 - q_B)^{N_i^B} \quad (2)$$

The probability of i being successfully influenced about Brand A *only* is given by $p_i^A(1 - p_i^B)$.

Given being influenced, adoption of A occurs immediately. A similar rule holds for brand B. The probability of i being informed about both products is $p_i^A p_i^B$, and in this case, she will adopt according to the ratio of probabilities α . Therefore, the probabilities of i adopting brand A, or brand B, or neither are given respectively by the following:

$$P_i(\text{adopt A}) = p_i^A(1 - p_i^B) + \alpha_A p_i^A p_i^B \quad (3)$$

$$P_i(\text{adopt B}) = p_i^B(1 - p_i^A) + \alpha_B p_i^A p_i^B \quad (4)$$

$$P_i(\text{adopt none}) = (1 - p_i^B)(1 - p_i^A) \quad (5)$$

$$\text{where } \alpha_A = \frac{p_i^A}{p_i^A + p_i^B}, \alpha_B = 1 - \alpha_A \quad (6)$$

In the simulation, the realization of the adoption probability was done through drawing, for each unit in each period, a random number from a uniform distribution and comparing it to the adoption probabilities P_i^A and P_i^B .

We have also aimed for consistency with previous research regarding the ranges of δ and q that we examine (see for example Goldenberg et al. 2007). In previous research, the ranges of δ and q were generally chosen with the goal of arriving at aggregate-level adoption curves that were consistent with empirical market-level findings. The levels of δ have been quite stable across applications, whereas due to the network-dependent nature of the internal influence, q has varied in different studies according to network structure parameters, for example average degree and network size.

While some studies have focused on the question of whether a new product manages to penetrate the market (Watts and Dodds 2007), we follow the diffusion framework that assumes that eventually, the vast majority of the market potential adopts the product. Thus, the range of q was chosen to ensure that within the 30 periods we analyzed, we arrived at a reasonable percentage of adopters. Thus, most of the acquisition comes from customers who, without the seeding programs, would have adopted the competing brand, rather than from persistent non-adopters who decided to adopt. This enables us to distinguish more clearly between acceleration and acquisition processes. We have mostly used the same range for q across all networks, varying it only in the two cases in which the network average degrees differed considerably from those of the rest of the networks (see parameter ranges in Table 2).

We note that other operationalizations of the diffusion process can be envisioned. In sociology, for example, *threshold models* have also been used to model diffusion processes. These models assume that an individual adopts an innovation only when a certain number of others who pass her threshold have done so (Deffuant, Huet, and Amblard 2005). In contrast, *cascade models* such as the one used here (see Leskovec, Adamic, and Huberman 2007) take an approach that follows the basic diffusion-of-innovations tradition in the spirit of the Bass model and its extensions. This approach enables us to incorporate external effects such as advertising, which are traditionally not a part of the threshold adoption approach. Because it follows a well-established research tradition in marketing, the cascade approach also enables us to build on past research when setting up and calibrating model parameters. Interestingly, recent simulations focusing on the role of influentials in new product diffusion have shown that the two modeling approaches yield similar results (Watts and Dodds 2007).

Note

1. We thank Dr. Michael Wu, principal scientist at Lithium, for his help in data gathering and analysis, and his wise advice during the process.

References

- Boguña, M., R. Pastor-Satorras, and A. Diaz-Guilera (2004), "Models of Social Networks Based on Social Distance Attachment," *Physical Review E* 70(056122): 1–8.
- Burt, Ronald S. (1999), "The Social Capital of Opinion Leaders," *The Annals of the American Academy of Political and Social Science* 566(1), 37–54.
- Carl, Walter J., ed. (2007), *Measuring Word of Mouth, Volume 3*. Chicago: Word of Mouth Marketing Association.
- 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.
- De Bruyn, Arnaud, and Gary L. Lilien (2008), "A Multi-Stage Model of Word of Mouth Through Viral Marketing," *International Journal of Research in Marketing* 25(3): 143–225.
- de Valck, Kristine, Gerrit H. van Bruggen, and Berend Wierenga (2009), "Virtual Communities: A Marketing Perspective," *Decision Support Systems* 47(3): 185–203.
- Deffuant, Guillaume, Sylvie Huet, and Frédéric Amblard (2005), "An Individual-Based Model of Innovation Diffusion Mixing Social Value and Individual Benefit," *American Journal of Sociology* 110(4): 1041–1069.
- Delre, S.A., W. Jager, T.H.A. Bijmolt, and M.A. Janssen (2007), "Targeting and Timing Promotional Activities: An Agent-Based Model for the Takeoff of New Products," *Journal of Business Research* 60(8): 826–835.
- De Matos, Ceslo Augusto, and Carlos Alberto Vargas Rossi (2008), "Word-of-Mouth Communications in Marketing: A Meta-Analytic Review of the Antecedents and Moderators," *J. of the Academy of Marketing Science*, 36, p. 578.

Dunn, Lucinda (2007), "Identifying Influencers in the Digital Age: The Uploader Research." In *Measuring Word of Mouth, Volume 3*, ed. Walter J. Carl. 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.

Gilbert, Nigel, Wander Jager, Guillaume Deffuant, and Iqbal Adjali (2007), "Complexities in Markets: Introduction to the Special Issue," *Journal of Business Research* 60(8): 813–815.

Godes, David, and Dina Mayzlin (2004), "Using Online Conversations to Study Word Of Mouth Communication," *Marketing Science* 23(4): 545–560.

Godes, David, and Dina Mayzlin (2009), "Firm-Created Word of Mouth Communication: A Field-Based Quasi-Experiment," *Marketing Science* 28(4): 721–739.

Godes, David, Dina Mayzlin, 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): 415–428.

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.

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2002), "Riding the Saddle: How Cross-Market Communication Can Create a Major Slump in Sales," *Journal of Marketing* 66(2): 1–17.

Goldenberg, Jacob, Barak Libai, and Eitan Muller (2010), "The Chilling Effects of Network Externalities," *International Journal of Research in Marketing*, forthcoming.

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, 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.

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, 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.

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.

Hogan, John E., Katherine N. Lemon, and Barak Libai (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 (2008), “Opinion Leadership and Social Contagion in New Product Diffusion,” MSI working paper 08-004.

Keller, Ed (2007) “Unleashing the Power of Word of Mouth: Creating Brand Advocacy to Drive Growth,” *Journal of Advertising Research* 47(4): 448–452.

Keller, Ed, and John Berry (2003), *The Influentials*. New York: Free Press.

Kiss, Christine, and Martin Bichler (2008), “Identification of Influencers: Measuring Influence in Customer Networks,” *Decision Support Systems* 46, 233–253.

Kumar, V., Andrew Petersen, and Robert P. Leone (2007), “How Valuable is Word of Mouth?” *Harvard Business Review* 85(10): 139–146.

Kumar, V., Andrew Petersen, and Robert P. Leone (2009), "Exploring the Effectiveness of Marketing Communications on Customer Buying and Referral Behavior," working paper, University of North Carolina-Chapel Hill.

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.

Libai, Barak, Eitan Muller, and Renana Peres (2009a), "The Diffusion of Services," *Journal of Marketing Research* 46(2): 163–175.

Libai, Barak, Eitan Muller, and Renana Peres (2009b), "The Role of Within-Brand and Cross-Brand Communications in Competitive Growth," *Journal of Marketing* 73(3): 19–34.

Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing* 70(July): 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.

Macy, Michael W., and Robert Willer (2002), "From Factors to Actors: Computational Sociology and Agent-Based Modeling," *Annual Review of Sociology* 28(August): 143–166.

Marsden, Paul (2006), "Seed to Spread: How Seeding Trials Ignite Epidemics of Demand." In *Connected Marketing: The Viral, Buzz, and Word of Mouth Revolution*, ed. Justin Kirby and Paul Marsden. Oxford, UK: Butterworth-Heinemann.

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 (2008), "Asymmetric Social Interactions in Physician Prescription Behavior: The Role of Opinion Leaders," Stanford University Graduate School of Business Research Paper No. 1970.

North, Michael J., and Charles M. Macal (2007), *Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation*. New York: Oxford University Press.

Peres, Renana, Eitan Muller, and Vijay Mahajan (2009) "Innovation Diffusion and New Product Growth: Critical Review and Research Directions," *International Journal of Research in Marketing*, forthcoming.

Quinton, Brian (2008), "Enter the Dragon," *Promo*, October 1.

Rosen, Emanuel (2009), *The Anatomy of Buzz Revisited: Real-Life Lessons in Word of Mouth Marketing*. New York: Broadway Business.

Rust, Roland T., and Tuck Siong Chung (2006), "Marketing Models of Service and Relationships," *Marketing Science* 25(6): 560–580.

Sarkar, Palash (2000), "A Brief History of Cellular Automata," *ACM Computing Surveys* 32 (1): 80–107.

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.

Summerfield, Patti (2007), "Pass It On: Canada's WOM ROI Earns its Own Budget Line," *Strategy*, February 1.

Tegler, Eric (2009), "Ford Counting on Army of 100 Bloggers to Launch New Fiesta," *Advertising Age*, April 20.

Tesfatsion, Leigh (2003), "Agent-Based Computational Economics: Modeling Economies as Complex Adaptive Systems," *Information Sciences* 149(4): 262–268.

Thompson, Scott A., and Rajiv K. Sinha (2008), "Brand Communities and New Product Adoption: The Influence and Limits of Oppositional Loyalty," *Journal of Marketing* 72(6): 65–80.

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.

Valente, T.W., S. Watkins, M.N. Jato, A. Van der Straten, and L. 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, 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: 530–544.

Van den Bulte, Christophe, and Stefan Wuyts (2007), *Social Networks and Marketing*. Cambridge, MA: Marketing Science Institute.

Van den Bulte, Christophe (2010), *Opportunities and Challenges in Studying Customer Networks*. In *The Connected Customer*, ed. Stefan Wuyts, Marnik G. Dekimpe, Els Gijsbrechts, and Rik Pieters. London: Routledge.

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.

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.

Watts, Duncan J., and Peter Sheridan Dodds (2007), “Influentials, Networks, and Public Opinion Formation,” *Journal of Consumer Research* 34(4): 441–458.

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

Table 1: Network characteristics

	Network name	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	1,133	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	Friendship among Cameroonian women	Valente et al. 1997	161	6.0	13.9	3.2	.128
Networks collected for this study								
4	Retailer	Lithium online customer network		4,968	8.8	60.0	3.5	.502
5	Services	Lithium online customer network		4,457	13.5	98.6	2.8	.481
6	High tech 1	Lithium online customer network		3,574	2.6	16.4	2.8	.145
7	High tech 2	Lithium online customer network		3,663	2.6	15.8	3.4	.176
8	Entertainment 1	Lithium online customer network		1,496	5.3	33.5	3.5	.285
9	Entertainment 2	Lithium online customer network		7,045	4.2	28.4	3.6	.239
10	YouTube	Social networking site		4,160	8.5	30.2	4.0	.073
Empirical-degree random networks								
11	Keller Fay	Based on the ongoing TalkTrack WOM survey	Keller 2007	1,000	6.0	17.7	5.0	.056
12	CNET	One-time survey on social networks	Smith et al. 2007	1,000	42.2	106.9	2.2	.110
	Average			3,611	9.5	39.6	3.8	.22
	Standard deviation			3027	10.8	32.0	1.4	.14

Table 2: Parameter ranges

Parameter	Range
δ (external influence)	.001, .005, .01, .015, .02
q (internal influence)	Cameroon: .16, .2, .24, .28, .32 CNET: .005, .01, .02, .03, .04 The rest: .04, .08, .1, .12, .16
Program size (proportion of market)	.005, .01, .02, .03, .04, .05
Program type	Random, Influential

Table 3: Customer equity and number of adopters for random and influentials programs: A Keller Fay-based network

	1	2	3	4	5	6
	Customer equity (\$) Brand A	Customer equity (\$) Brand B	Total customer equity (\$)	% gain Brand A*	No. of final adopters Brand A	No. of final adopters Brand B
Scenario						
1. No seeding program	222.3	224.9	447.2		482	489
2. Random seeding A	368.8	129.8	498.6	65.9%	725	253
3. Random seeding A & B	259.4	260.3	519.7	16.7%	491	490
4. Influentials seeding A	439.1	97.8	536.9	97.5%	797	184
5. Influentials seeding A & B	281.8	279.4	561.2	26.7%	493	489

* Compared to the no program option (first row)

Table 4: Gains to brand A for a brand A-only program across networks compared with no-program scenario

No.	Network name	1) Gain random program A	2) Gain random programs A&B	3) Gain influentials program A	4) Gain influentials programs A&B	5) Acceleration Ratio* random A	6) Acceleration Ratio* influential A
1	URV e-mail network	75.0%	12.8%	100.2%	18.7%	29.3%	33.7%
2	PGP	58.2%	14.0%	79.6%	17.4%	35.1%	38.3%
3	Cameroon Tontines	92.4%	23.8%	122.3%	28.7%	32.8%	36.4%
4	Retailer	91.9%	11.7%	114.3%	19.7%	20.3%	28.2%
5	Services	98.8%	8.5%	119.8%	16.6%	17.8%	25.5%
6	High tech 1	87.2%	10.3%	117.5%	15.8%	19.00%	31.1%
7	High tech 2	78.0%	10.5%	107.8%	16.6%	23.1%	32.6%
8	Entertainment 1	80.7%	11.8%	112.1%	19.4%	23.8%	32.1%
9	Entertainment 2	84.2%	8.9%	106.2%	16.0%	20.3%	28.0%
10	YouTube	78.7%	12.3%	108.3%	21.6%	27.6%	33.8%

11	Keller Fay	65.9%	16.7%	97.5%	26.7%	35.1%	41.4%
12	CNET	73.8%	13.8%	101.5%	22.1%	30.3%	36.0%
	<i>Average</i>	<i>80.4%</i>	<i>12.9%</i>	<i>107.3%</i>	<i>19.9%</i>	<i>26.2%</i>	<i>33.1%</i>
	<i>Standard deviation</i>	<i>11.5%</i>	<i>4.1%</i>	<i>11.7%</i>	<i>4.2%</i>	<i>6.3%</i>	<i>4.6%</i>

* Percentage of social value (equity gain) attributed to customer acceleration (rather than acquisition) for a Brand A-only program.

Figure 1: Customer acceleration ratio and net gain under a random seeding program of brand A with varying relative strength of Brand A

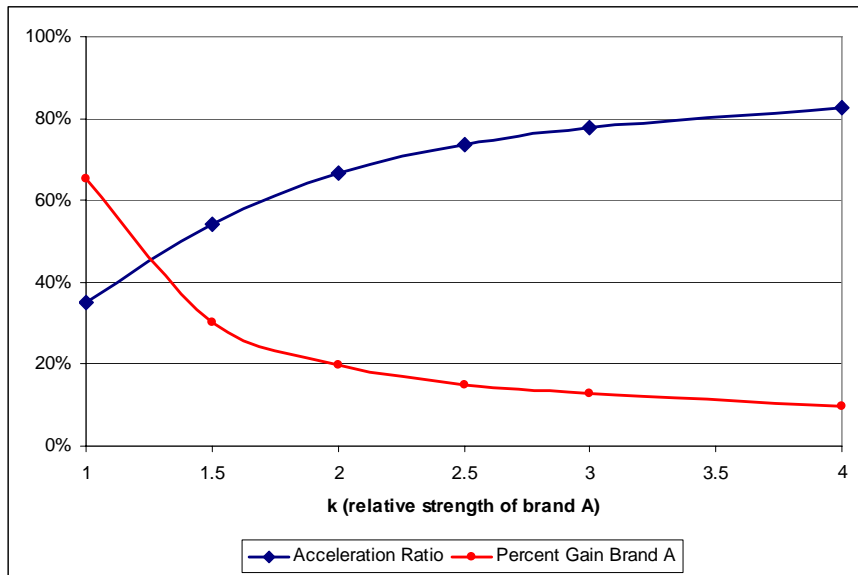


Figure 2: Social value in a single-brand-only program under multiple seed sizes. (Keller Fay network)- random and influential seeding programs

