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Targeting Revenue Leaders for a New Product

Historically, when targeting potential adopters of a new product, firms have tended to focus first on people with disproportional effect on others, often labeled "opinion leaders." The authors highlight the benefit of targeting customers with high lifetime value (CLV), or "revenue leaders." The authors argue that targeting revenue leaders can create high value both by accelerating adoption among these customers and because of the higher-than-average value that revenue leaders generate by affecting other customers with similarly high CLV. The latter phenomenon is driven by network assortativity, whereby people's social networks tend to be composed of others who are similar to themselves. Analyzing an agent-based model of a seeding program for a new product, the authors contrast revenue leader seeding with opinion leader seeding and compare the factors that influence the effectiveness of each. They show that the distribution of CLV in the population and the seed size play a major role in determining which seeding approach is preferable, and they discuss the managerial implications of these findings.

Keywords: word of mouth, opinion leaders, assortativity, customer lifetime value, agent-based models

Conventional wisdom in much of the business world (Keller and Berry 2003; Rosen 2009) suggests that when targeting potential adopters of a new product, firms should focus first on people with disproportional effect on others, often labeled "opinion leaders," "influentials," or "influencers." The idea is that getting to opinion leaders early will help accelerate the overall adoption process in the population. If we define "social value" as the long-term monetary value a person creates by affecting others, an opinion leader should have higher social value than an average person, and this difference should be most pronounced during the early stages of the product life cycle (Hogan, Lemon, and Libai 2003). Claims that influence in the population follows an unequal, "scale-free" distribution, particularly in online environments (e.g., Barabasi 2003), have further highlighted the importance of targeting opinion leaders.

Yet opinion leaders are not the only population it makes sense to target. One alternative, albeit less emphasized in the new-product literature, is to focus on people who can be expected to generate high profitability on their own. We refer to this population as "revenue leaders."[1] There are numerous indications across industries that consumer populations are characterized by a high variance in customer lifetime value (CLV)—that is, the expected profitability created by a given customer's purchases (Gupta and Zeithaml 2006). This makes the identification and targeting of high-CLV consumers an essential customer management tool (Bolton, Lemon, and Verhoef 2004; Kumar and Shah 2009). In particular, when introducing new products, an obvious benefit that firms can derive from targeting revenue leaders is the acceleration of these customers' adoption, which should create an earlier, larger cash stream and thus increase profits.

Notably, previous research has not compared the implications of targeting revenue leaders versus opinion leaders. An evolving literature, encompassing multiple disciplines, such as marketing (Zubcsek and Sarvary 2011), computer science (Kempe, Kleinberg, and Tardos 2003), and economics (Galeotti and Goyal 2009), has investigated optimal targeting of new products in the presence of social networks. Yet these studies have largely focused on maximizing the number of people who are influenced to purchase and have generally assumed that all consumers affected are equal in terms of value to the firm.

In this article, we focus on the value created by revenue leaders by contrasting it with the value created by the traditionally targeted opinion leaders (using mostly hubs, or people who are connected to many others in the network). In particular, we argue that targeting revenue leaders may be profitable not only because of the value created by the acceleration of these customers' own purchases but also because revenue leaders create higher-than-average social value. The latter effect is due to "network assortativity"—a ubiquitous phenomenon observed in social networks, whereby people tend to be directly connected to others who are like them (Newman 2003). Network assortativity should lead to a correlation between the revenue a person generates

[1]Although the term "revenue leader" does not fully capture the costs associated with purchase-based profit, we decided against using the term "profit" to avoid any confusion with the term "social value." When costs are proportional to revenue, as is often the case, this is an appropriate label.

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and the revenue of others in that person's close social network (Haenlein 2011). Therefore, a revenue leader should be more likely than an average customer to have other high-revenue customers in his or her social network, which translates into greater social value.

An additional motivation for exploring the value of revenue leaders pertains to the difficulty associated with determining the value of opinion leaders. Specifically, studies have indicated that many of the connections in online social networking sites, a major source of customer interaction data, are not good representations of actual influence (e.g., Trusov, Bodapati, and Bucklin 2010) and thus may not provide good characterizations of actual consumption-related interactions among customers (Crain 2011; Van den Bulte 2010). In comparison, managers often have easier access to the data typically used in CLV modeling—for example, by relying on previous customer transaction data for similar products—and can make use of established statistical techniques to help identify customers whose lifetime value is expected to be high (Blattberg, Kim, and Neslin 2008; Gupta et al. 2006).

Our aim is thus to provide managers and researchers dealing with decisions regarding a new product launch with intuition about the value of approaching expected revenue leaders early on. When data on customer connectivity are not readily available (i.e., when opinion leaders are not easily identifiable), our approach can help managers understand the actual value created by targeting revenue leaders. In scenarios in which managers believe they can assess the identity of both revenue leaders and opinion leaders, the question of the utility of targeting each group emerges. To evaluate this trade-off correctly, managers should understand the extent of the social value created by revenue leaders as well as the factors that affect its magnitude. These questions form the basis of our investigation.

One of the challenges of such an inquiry lies in the need to consider the complex dynamics characterizing the spread of influence in a social system comprising many social networks and made up of customers with varying lifetime value. Social science researchers increasingly use agent-based models (ABMs; Goldenberg, Libai, and Muller 2002; Miller and Page 2007; Shaikh, Rangaswamy, and Balakrishnan 2006) to track the nonlinear processes associated with the spread of influence in large-scale social networks, and we follow this practice here. Specifically, we use the ABM approach to investigate the case of a firm that introduces a new product and compare the customer equity created when "seeding" the market early on with different customer targets. Some of our key insights include the following:

- Given the often-witnessed skewed distribution of the expected CLV, revenue leader seeding can be a sensible alternative to opinion leader seeding. The additional value of revenue leaders over random customers stems from both direct value (the value directly attributable to the acceleration of these customers' purchases) and social value (due to CLV assortativity—the tendency of high-CLV customers to associate with other high-CLV customers). Furthermore, in cases in which revenue leaders are not only more profitable but also more influential (i.e., are more persuasive) than the average customer, their value is even greater, making revenue leader seeding a highly attractive approach.
- The distribution of CLV in the population plays a particularly important role in determining the effectiveness of targeting revenue leaders because this distribution affects both customers' direct value and the social value created by assortativity.
- The total value of seeding revenue leaders compared with that of seeding opinion leaders is strongly affected by the size of the seed. In both cases, there is a "saturation effect" such that the marginal value contribution of each seeded customer decreases with seed size. However, the saturation effect is stronger for opinion leaders than for revenue leaders. Within the networks analyzed in our study, the total value of revenue leaders was higher than that of opinion leaders when seed size was greater than 1% of the population. The seed size also affects the dynamics of social value and direct value. For smaller seed sizes, the total value of revenue leaders is attributable mainly to these customers' social value, whereas for seeds that are greater than 1% of the population, the total value of revenue leaders is mainly composed of the seeded customers' direct value.
- In line with recent work that has pointed to the role of contagion in creating inequality in customer profitability (DiMaggio and Garip 2011), we observe that the dispersion of total value among customers is stronger than is suggested by conventional calculations in which only the lifetime value is taken into account (Homburg, Droll, and Totzek 2008; Zeithaml, Rust, and Lemon 2001). Due to assortativity-driven social value, revenue leaders bring in more profit than that generated by their purchases alone, and by comparison, customers with low CLV (revenue laggards) are even less attractive.

Background

Seeding programs, typically used to help marketers spread new products or ideas, are programs in which a firm encourages a group of target customers (the "seeds") to adopt a new product early on, with the goal of jump-starting the contagion process and enhancing it for other customers (Jain, Mahajan, and Muller 1995; Lehmann and Esteban-Bravo 2006). The characteristics of the most effective seeds have attracted much research interest. The literature on customer-to-customer interactions has devoted much attention to the role of opinion leaders (Iyengar, Van den Bulte, and Valente 2011; Trusov, Bodapati, and Bucklin 2010; Zubcsek and Sarvary 2011). Such studies have considered various types of opinion leaders, including hubs, or the people with the most connections to others (Goldenberg et al. 2009; Watts and Dodds 2007); people who are highly persuasive because they are well regarded by their peers or because they are experts (Iyengar, Van den Bulte, and Valente 2011; Keller and Berry 2003); and people who have an advantage because of their network position—for example, because they bridge subnetworks (Hinz et al. 2011; Stonedahl, Rand, and Wilensky 2010).

Research in the field of computer science, which has mainly focused on opinion leaders as targets of seeds, suggests that it is computationally complex to determine the optimal size of the seed and the specific consumers who should be targeted. As a result, researchers have made considerable efforts to formulate efficient algorithms toward this end (for recent reviews, see, e.g., Bonchi et al. 2011; Easley and Kleinberg 2010). Hubs are probably the most commonly considered target group academically and in practice, largely because they are the easiest to identify given some information on connectivity (Libai, Muller, and Peres 2013). Although the benefits of hub targeting have been questioned (Aral and Walker 2012; Watts and Dodds 2007), this approach is widely accepted in practice (Rosen 2009) and is supported by diverse academic research (Easley and Kleinberg 2010; Hinz et al. 2011).

Targeting Revenue Leaders

A component that has largely been missing from the discussion on the importance of opinion leaders in customer acquisition (for an exception, see Iyengar, Van den Bulte, and Valente 2011) is the assessment of the monetary value contribution of the consumers affected (Libai et al. 2010). Ultimately, the best targets for customer acquisition should be those who will bring the highest customer equity contribution to the firm (Villanueva and Hanssens 2007). The firm should therefore aim to maximize not merely the number of people affected but the customer equity that the affected customers ultimately generate.

In situations in which different customers bring similar value to the firm, as is the case, for example, in most viral marketing applications (Hinz et al. 2011), it may be less critical to identify the monetary value of "receivers," or customers affected by the seed. However, for many products, the profitability of different receivers, often measured according to CLV, can differ considerably. Although the distribution of CLV among customers varies across industries, findings from various markets point to the ubiquity of a significant variation in customer CLV (Gupta and Zeithaml 2006; Kumar and Shah 2009; Zeithaml, Rust, and Lemon 2001).

In the context of a new product launch, the straightforward advantage of targeting people with expected high CLV stems from their direct value: the value created by accelerating the cash streams of the targeted customers. Accelerating a larger future cash stream (a high-CLV person) can be more beneficial than accelerating the purchases of customers associated with lower cash streams. Notably, the current literature offers little insight into how direct value compares with the social value that customers create by affecting others. In particular, the answer may not be straightforward if there is a correlation between lifetime value and social value. In what follows, we explore the phenomenon of assortativity as a potential source of this correlation.

The Assortativity of CLV

Assortative mixing in networks reflects the tendency of members of a network to attach to others who are similar in some way (Newman 2002). It stems from the known phenomenon of homophily, which reflects people's tendency to be associated with people who are similar to them (McPherson, Smith-Lovin, and Cook 2001). A pervasive phenomenon in social networks, assortativity can substantially affect the diffusion process (Aral 2011). Assortativity has often been demonstrated with regard to degree distribution (i.e., the distribution of the numbers of network members' connections), and it can occur in association with other variables as well (Newman 2003).

Assortativity in customer social networks is supported by a rich literature across disciplines that points to the tendency of people to bond with similar others over a variety of characteristics, including age, gender, religion, attitudes, beliefs, education, and occupation (McPherson, Smith-Lovin, and Cook 2001; Rivera, Soderstrom, and Uzzi 2010). Therefore, it seems likely that assortativity plays an important role in the adoption of new products (Rogers 2003). For example, it has been argued that members of social networking sites may share preferences and interest in the same products (Hogg 2010; Lewis et al. 2008). Similarity in consumption among friends is reflected in the relationship between geographical location and consumption-related outcomes such as customer satisfaction (Mittal, Kamakura, and Govind 2004) and customer profitability (Reinartz and Kumar 2003) as well as in the way physical proximity among customers drives product adoption contagion.

Therefore, we can expect to observe a correlation between the purchase-based profitability of a customer and that of the members of his or her social network. We refer to this phenomenon as "CLV assortativity." Indeed, recent analysis constructed using the communication logs of cellular customers indicates a significant and substantial degree of positive network autocorrelation in customer-level revenue, whereby high- (low-) revenue customers tend to be primarily connected to other high- (low-) revenue clients (Haenlein 2011). This phenomenon can also help explain why referred customers tend to be more profitable than customers who arrive through marketing channels (Schmitt, Skiera, and Van den Bulte 2011).

An ABM of New Product Seeding

We next examine the case in which a firm introduces a new product and uses seeding early on to enhance the process. By examining the value created by different targeting strategies, we aim to better understand the relative value created by approaching revenue leaders. We begin with some fundamental aspects of our approach.

The Method: ABMs

A key challenge to exploring the issues raised previously lies in the need to take the full network into account. The social influence of a customer is not limited to his or her close social network but can spread by a ripple effect in which acquired customers with different CLV and social network positions further affect others. Simple linear analysis may be of limited utility in capturing the full extent of this influence.

To address this challenge, we use stochastic network-based cellular automata, an ABM technique that simulates aggregate consequences based on local interactions among individual members of a population (Goldenberg, Libai, and Muller 2002). We use ABMs to simulate events and aggregated outcomes in a "would-be world," in which relationships at the individual level are similar to those observed in the real world. Due to the role of social interactions in innovation diffusion, ABMs have been widely used to model the growth of markets for new products (Delre et al. 2010; Garcia 2005).

This framework is consistent with the context of our analysis, the diffusion of a new product, and the market outcomes that emerge as a result of the interaction of many people. Furthermore, as Rand and Rust (2011) note, an essential advantage of ABMs lies in their ability to consider multiple sources of heterogeneity among customers and to take into account their locations in different social networks. Here, the consumer's network position is a fundamental aspect of the analysis, and we study thousands of networks to capture possible effects of network heterogeneity, investigating numerous sources of individual-level heterogeneity. In addition, ABMs can provide insight regarding counterfactuals covering a wide parameter space by identifying conditions in which particular outcomes are to be expected. Therefore, ABMs are a practical tool for exploring the conditions that influence the effectiveness of revenue leader seeding versus opinion leader seeding. In Web Appendix I (www.marketingpower.com/jm_webappendix), we elaborate more on the specifics of our approach and how it compares with recent guidelines on verification and validation of ABMs (Rand and Rust 2011).

The Diffusion Process

Given that our context is new product growth, we must first define a diffusion process in which people adopt a new product. For this process, we use a stochastic cascade approach that follows the basic logic of the Bass diffusion model for the individual adoption process in social networks (Muller, Peres, and Mahajan 2009). Within this framework, two factors affect a consumer's adoption decision: an external factor, representing the probability of being influenced by advertising, mass media, or other marketing efforts, and an internal factor, representing the probability of being influenced by a social interaction (e.g., word of mouth) with another consumer who has already adopted the product. Formally, the probability p_i that an individual i will adopt a given product in period t (contingent on not having adopted it before t) can be determined as follows:

$$p_i(t) = 1 - (1 - \delta_i)\,(1 - q_i)^{N_i(t)}, \tag{1}$$

where δ_i is the probability that actor i adopts the product due to external factors (external influence parameter), q_i is the probability that actor i adopts the product due to an interaction with one other person who has already adopted the product (internal influence parameter), and $N_i(t)$ is the number of people in i's personal network who have already adopted the product before t. In addition to being well accepted, an advantage of the cascade approach is that it follows an established tradition in marketing, which also allows us to build on prior research when setting up the model. This diffusion model framework is consistent with similar work in the marketing literature that uses ABMs to examine questions related to new product growth (Goldenberg et al. 2007; Libai, Muller, and Peres 2013). We discuss the approach and the choice of parameter ranges further in Web Appendix II (www.marketingpower.com/jm_webappendix).

The Seeding Alternatives

We examine three options for the seed selection process. The first is random seeding, in which the seed customers are chosen randomly among potential customers. The second approach is opinion leader seeding. Following the preceding discussion, we focus first on hub seeding, in which the seed customers are chosen according to how many connections they have (i.e., their degree, or the size of their individual social network). In line with previous research in this area, we consider hubs the top 10% of customers with the largest degrees (Watts and Dodds 2007) and randomly choose the seed from among this group. Subsequently, we also examine, as a robustness check, the consequences of targeting people who are not necessarily hubs but are highly persuasive on an individual level. The third approach is revenue leader seeding, in which we chose the seed customers from among the customers with the highest expected CLV. To be consistent with the opinion leader case, we consider the top 10% in terms of CLV revenue leaders and randomly seed among them.

The Value Created by the Seeding Program

We define the profitability of a seeding program as the difference in customer equity between a diffusion process without seeding and one that includes seeding. Consistent with theoretical work on seeding in the diffusion of innovations paradigm (Ho et al. 2012; Jain, Mahajan, and Muller 1995), the difference in profitability stems from acceleration of the adoption process (because all the market potential will eventually adopt), which translates to profit through the discount rate.

We assume that the total value created by a seeding program is composed of three components: direct value, social value, and the cost of seeding. Direct value, as noted previously, is the value directly attributable to the acceleration of the adoption of the seeded consumers. The social value of the seeded consumers is the monetary value created by their social interactions (Ho et al. 2012; Kumar et al. 2010; Libai, Muller, and Peres 2013; Wangenheim and Bayon 2007). It stems from the acceleration of others in addition to the seeded consumers. The cost of seeding (program cost) stems from two sources: the cost of identifying the target group and the means needed to convince those consumers to adopt early. The latter cost is highly variable across seeding programs and can include advertising, discounts, samples, or even free products (Rosen 2009). The overall value of the seeding program is thus represented by the following:

$$\text{Total Value} = \text{Direct Value} + \text{Social Value} - \text{Cost of Seeding}. \tag{2}$$

To focus on the dynamics of value created, in the following analysis, we assume no cost of seeding. Subsequently, we consider the question of how program costs can affect the choice of target.

Measurement of Social Value

Given a social network and a seeding program, it is difficult to assess social value directly because of the multiple stochastic interactions that occur in the network following adoption by the seed. However, we can compute the values of the other components of Equation 2 and deduce the social value as follows: We simulate each adoption process twice, without seeding (referred to as "base diffusion") and with seeding. This results in two vectors of adoption times for each node (to avoid the consequences of random variation, we simulate each parameter combination 60 times). We subsequently discount each node's revenue according to its adoption time, using a discount rate of 10% per period. Subtracting the discounted revenue under no seeding from the discounted revenue under seeding gives the total value of the program. The direct value of the seed is computed as the difference between the two simulations in the net present value (NPV) of the seeded people. Assuming no program cost, we can subtract the direct value from the total value to obtain the social value of the seed.

Measuring Social Value: An Example of the Cellular Market in a European Country

To demonstrate the measurement of social value and its dynamics, we begin with an empirical illustration. It is not trivial to obtain access to a data set that includes both the social network structure of customers and a measure of customer profitability. Although researchers are increasingly able to use large-scale social network data for academic analysis, much of these data are not directly related to consumption of products and certainly do not include measures of customer profitability. However, one area in which such data may be more available is the telecommunications industry. Telecommunications databases are increasingly used to capture social networks of customers (Eagle, Pentland, and Lazer 2009; Hill, Provost, and Volinsky 2006) and typically contain information on consumption, at least in terms of the periodic bill, and as such can serve as a relevant example for our case.

We had access to a database of a sample of cellular customers in a European country; these data were used in Haenlein (2011). Two customers in the network were considered connected if there was communication between them; we considered only communications that represented at least 1% of either customer's total call duration, to exclude incidental calls. The network included 6,680 customers, whom we chose using a snowball algorithm (for additional details on the data collection process, see Haenlein 2011). On the basis of customers' individual monthly bills, in addition to data we had on retention, we were able to construct an assessment of the CLV for each person in this network, using the basic CLV formula (Gupta, Lehmann, and Stuart 2004; for more details, see Web Appendix III at www.marketingpower.com/jm_webappendix). We normalized the average customer CLV to 1. The Pearson correlation coefficient between the CLV of one person and the CLV of all actors directly connected to this person, who serves as a measure of the degree of assortativity in consumption, equals .35.[2]

On this network, we simulated the growth of a new product under different seeding programs, targeting random customers, opinion leaders, or revenue leaders. For each simulation, we assessed the social value of the seed as described previously. We conducted all simulations within the R Computing Environment (for the full R-code used to run our ABM simulation, see Web Appendix IV at www.marketingpower.com/jm_webappendix).

Using this data set, Figure 1 shows the average social value per percent of seeding, that is, the percentage of the total population who were selected as seeds. Researchers have mentioned seeding the market with 1% of the customers as an industry rule of thumb (Marsden 2006; Rosen 2009); however, others have advocated larger percentages (Jain, Mahajan, and Muller 1995). Here, we show the effects of 1%, 2%, and 3% seeding on social value. We observe that the social value created by revenue leader seeding is higher than that of random seeding but lower than that of opinion leader seeding. We also observe a saturation effect of seeds (Zubcsek and Sarvary 2011): the marginal value contribution of each seeded customer decreases. It is notable that the magnitude of this saturation effect varies across different seeding strategies. This means that seed size should be taken into account when evaluating the effectiveness of the different strategies.

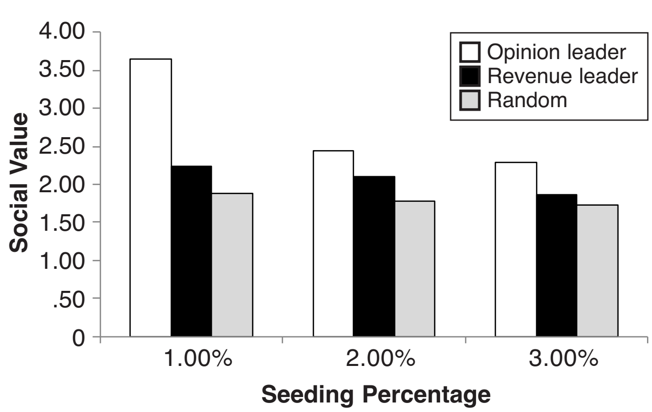
Our example from the cellular industry reflects a specific network with a specific customer profitability distribution. Next, we generalize these findings across network structures and customer profitability distributions and directly compare the profitability implications of the various strategies.

Evaluating Seeding Strategies for Different Networks

Network Structure

Although early work on ABMs uses simple network structures, such as eight-cell neighborhoods in the classical cellular automata, marketing researchers would naturally want to ensure that the social networks used for their analysis are good representations of the actual types of social networks found in the marketplace. To create the social networks that

FIGURE 1
European Cellular Service Provider: Social Value Created Under Different Seeding Percentages



Notes: As a comparison, average CLV in the population = 1.

[2]It should be noted that telecom services may have a higher-than-average assortativity in CLV because the revenue is generated from the presence of ties. Still, recent empirical results that point to even higher assortativity levels of .54 and .57 among physicians (Iyengar, Van den Bulte, and Valente 2011) suggest that this market is not exceptional in its revenue assortativity level.

form the basis for our analysis, we used an algorithm Jackson and Rogers (2007) propose. This algorithm creates links among nodes in a way that replicates link formation in actual social networks (for more information on the Jackson Rogers model and the range of parameters used to simulate the networks in our study, see Web Appendix V at www.marketingpower.com/jm_webappendix).

The Distribution of Customer Profitability

To model profitability in our simulated networks, it was necessary to make decisions with regard to two consumption-related variables. We discuss them in the following subsections.

The standard deviation of the CLV distribution. The first decision refers to the distribution of customer profitability in the network. We used a lognormal distribution, which is well suited to modeling customer-level revenue because it is flexible enough to account for the highly right-skewed distribution curves observed in many empirical settings (Fader, Hardie, and Lee 2005; Schmittlein and Peterson 1994). In particular, we relied on a lognormal distribution in which the mean of the underlying normal distribution was equal to zero, and we varied the standard deviation (SD) of the underlying normal distribution as a design factor. We considered eight values between .10 and 1.75 for the SD of the underlying normal distribution.[3] To make all distributions comparable, we scaled each to an average revenue of one. The actual SD of the CLV distribution resulting from (1) transforming the underlying normal distribution into a lognormal distribution and (2) adjusting it to reach a specified level of CLV assortativity (see the next section) varied between .10 and 4.02, with an average of 1.38 over all treatment cells. These values compare well to the SDs of value distributions previously reported in the literature (Kumar, Petersen, and Leone 2007, p. 143; Kumar and Shah 2009, Figure 4).[4]

The level of CLV assortativity in the network. Following common practice in the social network literature (Newman 2003), we measured CLV assortativity as the Pearson correlation between the CLV of a person and the CLV of the others to whom that person is connected. To account for different levels of CLV assortativity within our simulation, we iteratively modified actor-specific CLV values drawn from the underlying lognormal distribution to reach a prespecified target correlation value. We used eight values between 0 and .70 for the Pearson correlation coefficient between a node's own CLV and the average CLV of all other nodes connected to that node. These correlation values correspond to a degree of network autocorrelation, as measured by Moran's I (Moran 1950) between 0 and .46, with an average of .15 over all conditions. The degree of network autocorrelation assumed in our simulation is slightly more conservative than values previously reported in the literature (Haenlein 2011). Within our empirical analysis, the corresponding Pearson correlation coefficient is equal to .35, resulting in a Moran's I value of .29.

Results

We simulated our model using eight different values for each of the following variables: network clustering coefficient (i.e., the extent to which customers in the network tend to "cluster"; in other words, a reflection of the likelihood that a node's neighbors are also connected to one another), SD of the CLV distribution, CLV assortativity, and seed size. This resulted in 8 × 8 × 8 × 8 = 4,096 different scenarios. We ran each scenario 60 times, resulting in 245,760 growth processes taken into account. Table 1 presents descriptive statistics on the variables used in our analysis, which include both the design factors and network characteristics. Table 2 shows the average social, direct, and total value achieved through each seeding approach for different seed sizes (in percentage of the population).

Strength of Social and Direct Value

First, we observe that, on average across all simulations, the social value of the seed is highest for opinion leaders, followed by revenue leaders, and then by random customers. Note that although the social value of revenue leaders is higher than that of random customers, it is still considerably lower on average than the social value of opinion leaders. Second, the direct value of customers is highest for revenue leaders, followed by random customers, and then by opinion leaders. Notably, although we do not assume a difference in the CLV between an opinion leader and a random customer, the direct value of seeding opinion leaders is lower than that of seeding random customers. This phenomenon occurs because, in the absence of seeding, opinion leaders tend to adopt the product earlier because they are more connected and thus are exposed earlier to influence (Goldenberg et al. 2009). As a result, accelerating opinion leaders brings less direct value compared with accelerating random customers, who otherwise would have adopted later.

The Effect of Seed Size

We observe that in all cases, the marginal social value of the seed decreases considerably with seed size; this decrease is more pronounced for opinion leaders than for revenue leaders and random customers. In general, this decrease, or "saturation effect" (Zubcsek and Sarvary 2011), is expected to occur for any seeded population: when more customers are incorporated into the seed, their social networks are more likely to overlap with one another, which reduces the incremental value contribution of each customer in the seed. Thus, although the overall social value produced by the seed might grow, the social value per percentage of seed size (which we report here) will decrease.

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[3]The density of a lognormal distribution is:

$$f(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} e^{-\frac{(\log x - \mu)^2}{2\sigma^2}}.$$

Within this setting, we set $\mu = 0$ and vary σ as a design factor on eight levels (.10, .25, .50, .75, 1.00, 1.25, 1.50, 1.75).

[4]Note that these SDs of value distributions previously presented in the literature are based on aggregated CLV data on a decile level, which implies that the actual standard deviations of the underlying individual-level value distributions are likely to be larger. All SDs are based on CLV information that has been normalized to an overall average of one.

TABLE 1
Parameter Description and Range

	M	Mdn	SD
Regression Input			
Seed size (in %)	2.25	2.25	1.15
CLV SD	1.42	1.11	1.21
CLV assortativity	.35	.35	.23
Degree SD	9.86	6.94	8.60
Degree assortativity	.63	.66	.12
Clustering coefficient	.24	.20	.15
CLV–degree correlation	.01	.04	.33
Customer Network Characteristics			
Average degree	5.66	4.27	4.16
Average degree opinion leader	31.00	23.40	23.96
Average CLV revenue leader	3.83	3.44	2.29

Design Factors	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8
Seeding percentage (in %)	.50	1.00	1.50	2.00	2.50	3.00	3.50	4.00
Underlying CLV SD	.10	.25	.50	.75	1.00	1.25	1.50	1.75
CLV assortativity	.00	.10	.20	.30	.40	.50	.60	.70
Clustering coefficient	.07	.10	.13	.17	.23	.31	.40	.52

TABLE 2
Social and Direct Values for Different Seed Sizes (per 1% Seeding)

	Opinion Leader			Revenue Leader			Random		
Seed Size (%)	Social	Direct	Total	Social	Direct	Total	Social	Direct	Total
.5	67.4	4.9	72.3	34.2	28.8	63.0	24.6	7.6	32.2
1.0	42.6	5.0	47.6	27.3	28.2	55.5	20.9	7.4	28.4
1.5	32.3	4.9	37.2	23.0	27.5	50.5	18.4	7.5	25.8
2.0	26.5	4.9	31.4	20.6	27.6	48.2	17.1	7.3	24.5
2.5	22.6	5.0	27.6	18.4	27.3	45.7	15.7	7.3	23.0
3.0	19.9	4.9	24.8	16.7	27.0	43.7	14.1	7.2	21.9
3.5	17.0	4.9	21.9	15.0	27.3	42.3	13.5	7.2	20.7
4.0	15.4	4.9	20.3	13.8	27.2	41.0	12.9	7.3	20.2
Average	30.5	4.9	35.4	21.1	25.1	46.2	17.2	6.0	23.1

Determining the optimal seed size in a given population remains an open question. Although some studies on seeding have used seed sizes as high as 7% and 9% (Hinz et al. 2011; Jain, Mahajan, and Muller 1995), recent work has suggested that the saturation effect may be rather strong and that the optimal seed size should be much lower (Aral, Muchnik, and Sundararajan 2011). However, our interest here is not in seeding percentage per se but in the specific relationship between seed size and the effectiveness of seeding opinion leaders versus revenue leaders.

Table 2 shows how the value produced by seeding opinion leaders, revenue leaders, and random customers varies as a function of seed size. First, we observe that the saturation effect associated with opinion leader seeding is stronger than that associated with random seeding (i.e., see the decrease rate of total value for opinion leaders vs. random customers). This may be because, compared with random customers, opinion leaders affect larger groups of people, and therefore, their social networks are more likely to overlap. The saturation effect is further enhanced by degree assortativity, whereby people tend to be in direct contact with others whose degrees are of similar size (Jackson and Rogers 2007; Newman 2003). This means that opinion leaders tend to be socially connected to other opinion leaders. As a result, as seed size increases, customers who would otherwise have been affected by the seed, thus increasing its social value, are more likely to be incorporated into the seed.

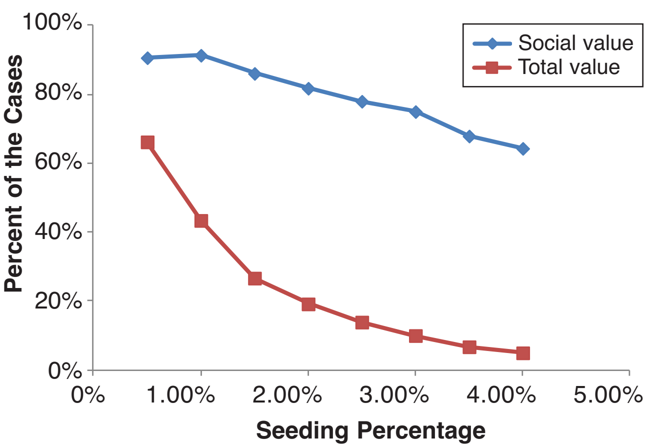
In revenue leader seeding, the saturation effect is also somewhat stronger than that in random customer seeding. This may be due to the effect of CLV assortativity, similar to the effect of degree assortativity among opinion leaders. (The effect of degree assortativity is similar for revenue leaders and for random customers.) Specifically, as the seed size goes up, the same people who are expected to be accelerated and bring social value are seeded themselves. Thus, when the seed is larger, the social network that a seeded revenue leader can influence may be smaller and less profitable. We note, however, that the saturation effect among revenue leaders is smaller than that among opinion leaders.

The Dynamics of Total Value

Given the preceding findings, we observe that when the seed size increases, the total value of opinion leader seeds (per percent seed) decreases more rapidly compared with that of revenue leader seeds. In the social networks we examine, for small seed sizes (<1%), the total value of opinion leaders is higher than that of revenue leaders, but for larger seeds, revenue leaders have a higher total value. Figure 2 shows, for different seed sizes, the percentage of cases in which opinion leader targeting provides higher social and total value than revenue leader targeting. Whereas the social value of opinion leaders is higher than that of revenue leaders in most cases, for seeds that are equal to or larger than 1% of the population, revenue leaders create more total value in at least 50% of cases.

Table 2 also indicates the composition of total value created by targeting revenue leaders. Consider a seed size of 1%. The social value and the direct value created by revenue leaders are roughly the same. However, if we consider the net gain over seeding random customers (with a seed size of 1%), of the 27.1 units of profit gain created (55.5 units – 28.4 units), approximately 6.4 stem from extra social value (i.e., due to CLV assortativity) and 20.8 from extra direct value. For larger seed sizes, the role of extra social value goes down, and the majority of the extra total value stems from direct value.

FIGURE 2
Percentage of Cases in Which Opinion Leader Social Value and Total Value Is Larger Than That of Revenue Leader, by Seed Size



Drivers of the Differences Between Revenue Leaders and Opinion Leaders

To shed more light on the drivers of the differences in the outcomes achieved when seeding opinion leaders versus revenue leaders, we ran a regression in which the dependent variable was the difference between the two approaches in the total value created. Our main aim was to investigate how network structure and customer profitability characteristics affected this difference. To evaluate the effect of network structure, we used three network-related variables. The first is the clustering coefficient, defined previously, which is a basic network measure that has a considerable effect on the speed of the spread of adoption in a social network (Van den Bulte and Wuyts 2007). The second is the SD of the degree distribution, which indicates to what degree the network is "scale free": the higher the SD, the larger the social networks of opinion leaders compared with the social networks of the rest of the population. The third variable is the degree assortativity (Newman 2003). To evaluate the effect of profitability characteristics, we used two variables: the SD of the CLV distribution and the CLV assortativity coefficient. We also included two additional variables as controls: the correlation between CLV assortativity and degree assortativity. Although such a correlation was not intentionally built into our settings, it was present in some of the many networks we considered. Naturally, when the correlation is high, we expect the difference in targeting between revenue leaders and opinion leaders to be smaller. Finally, we considered the seed size, which, as shown previously, can strongly affect the value the seeding program creates.

Table 3 presents the results of the ordinary least squares regression using the 4,096 observations. The adjusted R-square is .78, and all coefficients are significant at the .01 level. To elucidate the difference in effect size among variables, we report effect size using standardized coefficients, as well as Cohen's f^2 (Cohen 1992) and the eta-squared (Olejnik and Algina 2003). For each of these measures, a higher value indicates a larger effect size. Recall

TABLE 3
Regression Analysis: The Difference in Total Value Between Opinion Leaders and Revenue Leaders as the Dependent Variable

	Coefficient	Standardized Coefficient	t-Value	Partial eta-Squared	Cohen f^2
Intercept	–39.21	–39.21	–109.22		
Average clustering	–28.66	–4.25	–6.31	.0096	.0095
Degree SD	.41	2.77	4.07	.0040	.0038
Degree assortativity	–18.08	–1.58	–3.02	.0022	.0020
CLV SD	–28.15	–32.60	–90.38	.6665	1.9976
CLV assortativity	–24.07	–5.46	–15.19	.0534	.0562
CLV–degree correlation	10.59	2.02	5.57	.0075	.0073
Seed size	–2494.17	–28.58	–79.57	.6076	1.5480

Notes: N = 4,096; adjusted R^2 = .78; all coefficients significant at the .01 level. Test for homoscedasticity (nonconstant variance score test): χ^2 = 1227.547 on 1 d.f. (p-value < .00005); all variance inflation factors equal to or below 3.58; Durbin–Watson statistic = .29 (p-value < .00005); for a QQ plot, the distribution of studentized residuals, and spread-level plot, see Web Appendix VI (www.marketingpower.com/jm_webappendix).

that the dependent variable is the difference between the total value of opinion leaders and that of revenue leaders so that a negative coefficient implies that the corresponding variable contributes more to the value created by revenue leaders than to that of opinion leaders.

Two variables have particularly strong effects compared with the other variables. The first variable is the seed size (percentage of the population). The coefficient of the seed size is negative, indicating that when the seed is larger, revenue leader seeding yields more total value compared with opinion leader seeding. This outcome is consistent with our previous observations that social value per percent seed decreases faster with seed size for opinion leaders than for revenue leaders. The other variable is the SD of the CLV; a higher value for this variable implies that revenue leaders are more profitable compared with the rest of the population. The large negative effect of this variable indicates that when CLV SD is higher, targeting revenue leaders is more attractive—that is, yields more total value. This reflects the double benefit of targeting revenue leaders: these customers create direct value through acceleration of their own purchases, and in addition, through CLV assortativity, they bring in more social value. With regard to the other variables, we note that higher CLV assortativity indeed benefits revenue leader targeting more than it benefits opinion leader targeting.

Regarding the network structure variables, we observe that a higher clustering coefficient and a higher level of degree assortativity both benefit revenue leader targeting more than they benefit opinion leader targeting. In general, high clustering increases the speed of diffusion and thus increases profitability (Stonedahl, Rand, and Wilensky 2010). Recall, however, that social value is measured as the difference between the NPV created in the case of no seeding and the NPV in the presence of seeding. When clustering is higher, the diffusion rate might be expected to be higher even without intervention. Thus, in this case, seeding opinion leaders might have less of an effect than it would in a network in which clustering is lower; that is, diffusion is slower to begin with. We observed a similar effect for degree assortativity, which, like clustering, is more beneficial in the case of revenue leader seeding.

Our results also show that a higher SD of the degree benefits opinion leader seeding more than it benefits revenue leader seeding. Greater variability in the degree means that the social influence of opinion leaders is stronger compared with that of the rest of the population. Therefore, we expect a network with a high degree of SD to support rapid diffusion (and high profitability) even in the absence of seeding, thus reducing the contribution of the seed. Yet when opinion leaders are stronger, seeding ignites a more rapid diffusion process earlier, thus increasing the value of the seed. In our case, the combination of the two opposing effects ultimately favors opinion leader targeting; however, the effect size is not large.

Finally, we observe that a higher correlation between CLV and degree favors opinion leader seeding. This may be because in our sample, in more cases, revenue leaders create higher total value and not the other way around.

The Overall Value of Revenue Leaders and Opinion Leaders

Another way of comparing the different seeding strategies is to investigate their overall patterns of value creation. To do so, we determined the median total value created by either revenue leader seeding or opinion leader seeding. We define a "high" total value as a value above this point, and a "low" value as a value below this point. We then examined the average characteristics of cases in which a particular seeding strategy creates high or low value. Table WA7F in Web Appendix VII (www.marketingpower.com/jm_webappendix) presents a 2×2 matrix for the 512 combinations associated with 1% seeding (which is largely consistent with the industry standard seed size). Recall, however, that the seed size may affect the relative attractiveness of revenue leader and opinion leader seeding.

Compared with the regression analysis, such analysis is a much rougher indication of the roles of the different parameters in the total value created, and yet it does help shed light on some overall effects of CLV. Two things are especially noticeable. First, we again observe an indication of the power of the CLV distribution. In most cases in which a high value is achieved (Quadrants I and III in Web Appendix VII, Table WA7F), the CLV SD is relatively high, which means the profitability of revenue leaders is relatively high compared with that of the rest of the population. The role of CLV distribution seems stronger than that of the network parameters. Second, in many cases in which opinion leader seeding creates high value, revenue leader seeding creates high value as well. The relatively high correlation between CLV and degree in Quadrant I may help explain this issue.

Additional Analyses

Revenue Leaders ("Heavy Users") Exert a Stronger Influence

In the previous analysis, we focus on the number of connections as an indicator of influence; that is, we defined influentials as "social hubs" (Goldenberg et al. 2009). Although this approach is largely consistent with both managerial practice and academic research, there are alternative means of defining influentials. For example, an influential might be defined as someone who has a disproportional persuasion effect on the individual level. Such people might be experts, or their peers might highly value their opinions. Compared with the average customer, this type of influential has a higher probability of affecting others in any single interaction (Keller and Berry 2003).

This issue may be of particular significance in the context of our study due to a possible correlation between CLV and persuasiveness. Customers with high CLV can be considered "heavy users" of the product. These customers might therefore be perceived as experts and exert more influence on others than other customers (Kumar et al. 2010). Indeed, Iyengar, Van den Bulte, and Valente (2011) find that the more prescriptions a physician produces, the greater the likelihood that he or she will affect other physicians, and Hu and Van den Bulte (2012) find that heavy users and high-status adopters tend to exhibit higher within-tie contagiousness. If high-CLV customers are more influential than the average customer, the social value they create may be even higher than that assessed on the basis of assortativity alone.

To understand how such a phenomenon affects the main results, we reran our simulations, this time correlating the influence of a consumer to his or her CLV. Part 1 of Web Appendix VII (www.marketingpower.com/jm_webappendix) reports how the model was adjusted toward this end, and it presents the basic descriptive results on the types of value created (as in Table 2) in a case in which CLV is correlated to influence. As expected, correlating CLV with influence produced little change in the direct value or social value for opinion leader seeding and for random customer seeding. It did, however, substantially affect the social value of revenue leaders. This value was considerably larger than in our previous simulations for all seeding percentages. Furthermore, for 1% seeding and higher, revenue leaders had a higher social value compared with opinion leaders. This is because, in addition to being connected to more valuable customers, revenue leaders also had greater influence on them. Notably, in this scenario, revenue leaders had a higher total value than opinion leaders for all seeding percentages. Overall, it seems that when, in addition to correlating with CLV assortativity, CLV also correlates with influence, revenue leader targeting is an attractive option.

The Case of Revenue Laggards

Although targeting efforts are largely geared toward the more profitable customers, there is increasing managerial interest in managing the customers who are less profitable to the firm (Haenlein and Kaplan 2009; Haenlein, Kaplan, and Schoder 2006; Mittal, Sarkees, and Murshed 2008). Consequently, a better understanding of the implications of targeting revenue laggards (i.e., customers with lower CLV compared with others) can potentially benefit marketers. To examine the implications of seeding revenue laggards, we reran the analysis described previously, this time targeting the lowest 10% of customers in terms of CLV (see Table WA7E in Web Appendix VII at www.marketingpower.com/jm_webappendix). Our results for revenue laggards highlight the role of social value in widening the distribution of customer profitability, which is consistent with recent research showing how contagion processes help create inequality in customer value (DiMaggio and Garip 2011; Salganik, Dodds, and Watts 2006). As is evident here, due to social value, revenue leaders may be worth even more than their CLV would suggest, whereas revenue laggards are worth less. These findings emphasize the challenge firms face when managing a "customer pyramid" composed of different value tiers (Homburg, Droll, and Totzek 2008; Zeithaml, Rust, and Lemon 2001).

Additional Robustness Checks

We conducted a series of additional analyses to examine the robustness of our findings to several network-related assumptions in the model. In each case, we reran the analysis with the new condition. We present the basic results for each analysis, which correspond to the results in Table 2, in Web Appendix VII (www.marketingpower.com/jm_webappendix). Conditions we tested include a decay in the effect of a person's word of mouth (diffusion parameter q) over time following adoption (Web Appendix VII, Part 2), a periodic change in the level of word of mouth (diffusion parameter q, see Web Appendix VII, Part 3), and targeting of opinion leaders based on their word-of-mouth influence level (q) instead of degree (Web Appendix VII, Part 4). Generally, whereas the magnitude of the value varied, the direction of the results, as well as the relative strength of social and direct value in each case, were consistent with those shown in Table 2.

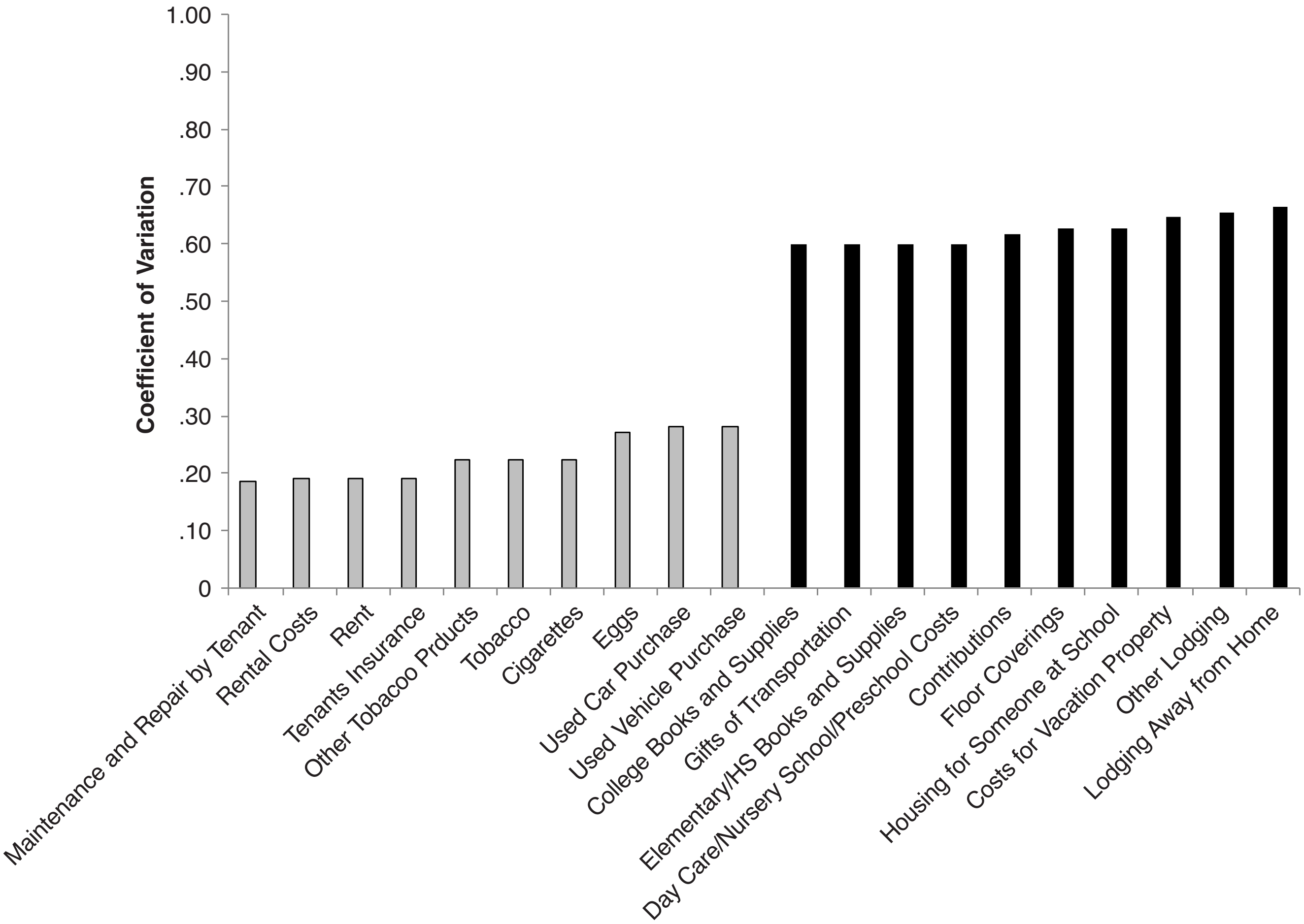
Discussion

Should a firm target revenue leaders or opinion leaders when seeding the market for a new product? Our results suggest that both revenue leader seeding and opinion leader seeding can create considerably greater value compared with random customer seeding. Our data indicate that the less explored option of revenue leader seeding is a viable alternative. In some cases, revenue leader seeding is the preferable option—for example, when the concentration of CLV is high or when the seed is large. In the following sections, we discuss several factors that can influence the benefit of targeting revenue leaders.

The Role of CLV Variation

The relatively strong effect of the distribution of customer CLV is a noteworthy result. In markets in which CLV is more concentrated (as reflected in a high SD of the CLV distribution), the total value of revenue leader seeding will be higher due to both direct and social value. Despite the evidence of high concentration in customer profitability (Mulhern 1999), the level of concentration can vary substantially across markets. Geographical analysis can provide indications of intercategory variance in CLV, which can be a helpful resource for managers in assessing the CLV variation for a new product. To demonstrate this issue, we obtained data from Applied Geographic Solutions, a company that analyzes consumption patterns on the basis of geographical location. The U.S.-based data refer to the consumption of 495 product types and encompass the majority of U.S. consumers. The company provides these data at the census block level, which is the smallest unit of analysis reported by the U.S. Census Bureau. We were able to obtain data on all 208,703 census block groups in the United States for each of the 495 product types. For each product type, we calculated the coefficient of variation (SD divided by the mean) of the yearly consumption in dollars per person. This enabled us to identify the relative variation in consumption across different products. Figure 3 presents 20 product categories, 10 with a particularly high coefficient of variation in consumption (high-disparity products) and 10 with a particularly low one (low-disparity products). The consumption variation of high-disparity products is more than two times greater than that of low-disparity products.

FIGURE 3
Extent of Variation in Consumption Across Geographical Areas in the United States



Note that such analysis may be helpful not only for identifying CLV distribution but also for assessing the strength of assortativity. Although caution is warranted when interpreting proximity among adopters as contagion (Iyengar, Van den Bulte, and Choi 2011), it is clear that even in the era of the Internet, geographical proximity has substantial influence on people's consumption-related social network of influence (Choi, Hui, and Bell 2010). Thus, in a geographical area where consumers' average CLV for a product is relatively high, there is a greater chance that a receiver of social influence will have high CLV as compared with consumers in areas where the average CLV is low. According to Figure 3, the relative social value of floor covering consumers (a high-disparity product) may be higher than tenants' insurance consumers (a low-disparity product). Given that marketers can access this type of geographical data straightforwardly, the analysis can be expanded to examine the extent to which assortativity is expected for different product categories.

Variation in CLV Assortativity

The added social value created by revenue leader seeding (beyond that of random seeding) stems from CLV assortativity. Assortativity, like CLV distribution, may vary across markets. For example, CLV assortativity should be especially dominant for products associated with a strong effect of peer pressure, such as tobacco and alcohol. In general, we expect it to be prevalent in product domains in which products help people infer and signal their identity, such as music, automobiles, hairstyles, and clothing, in contrast to lower-impact identity domains such as toothpaste and dish soap (Berger and Heath 2007). Although high-identity domains are also those from which people want to diverge to *not* look like some others (Berger and Heath 2007), we can expect that the groups from which people attempt to distinguish themselves are not necessarily part of their close social networks. Significant assortativity can also be expected for product domains in which people purchase together and affect one another's decisions (Kurt, Inman, and Argo 2011).

Another factor influencing CLV assortativity is incentives: it may be less ubiquitous in incentivized interactions—that is, if a person has an exogenous motivation to promote the product. For example, "buzz agents" who are motivated to spread the word on a new product to many others (Godes and Mayzlin 2009) may promote products they do not regularly consume and thus affect people outside their social network, who may differ from them in many ways. This issue may directly affect the relationship between lifetime value and social value. Kumar, Petersen, and Leone (2007), for example, find a nonmonotonic relationship between lifetime value and referral-related profits in the case of a referral reward program for mature services. The motivation to use a referral reward program and to approach specific others may be different from the mechanics underlying organic word of mouth; it may be dependent on the deal proneness of consumers and the structure of the referral incentive (Ryu and Feick 2007). Although assortativity may have some effect in such environments, exploring it in the context of specific reward systems is beyond our scope.

The Role of Network Variables

It is notable that, compared with CLV distribution, the network variables in Table 3 have a relatively small effect on the difference in total value between opinion leader seeding and revenue leader seeding. We might expect that network variables would especially affect the value of opinion leader seeding. However, in our context, social value is calculated as the difference between seeding and no seeding, and because the network variables affect the NPV of no seeding in the same direction (e.g., the case of clustering), the effect may be lower than expected.

However, this phenomenon may change in some settings—for example, if opinion leaders would tend to be less affected by others, as several studies have suggested (Aral and Walker 2012; Hu and Van den Bulte 2012; Van den Bulte and Joshi 2007). If this is the case, the value of the base diffusion process (without seeding) will go down, and the social value of seeding opinion leaders will go up. More research is needed on the extent of the phenomenon to incorporate it into approaches such as ours and understand its implications for total value analysis.

Another issue is that contagion processes in online environments, as opposed to offline environments, might be better served by opinion leader seeding. In online viral marketing campaigns, for example, the aim is often to raise consumers' awareness or to encourage a one-time purchase and further forwarding, and the distribution of CLV is not an issue. In addition, some online environments have a skewed scale-free distribution of degree, in which one person can affect many others through social media tools such as Facebook and Twitter. Bernoff and Schadler (2010), for example, suggest that a small group of so-called mass connectors is responsible for a large part of the impressions in social media and recommendation sites. The networks we analyze do not capture the effect of mass connectors. In addition, in an online environment, an actor is likely to have many connections that are not necessarily similar to him- or herself, and as a result, the level of CLV assortativity may be lower than that in offline social networks. This further suggests that opinion leader targeting may be preferable to revenue leader targeting in some online environments.

Identifying Opinion and Revenue Leaders

The decision to seed revenue leaders or opinion leaders is fundamentally dependent on the firm's ability to reach and affect the target groups. Obtaining data on opinion leader targeting, for example, is far from trivial. When the number of customers is small, firms can ask consumers to self-identify as opinion leaders (Vernette 2004), though marketers should be cautious about this procedure given recent research that questions the validity of self-reports as measures of opinion leadership (Iyengar et al. 2011; Iyengar, Van den Bulte, and Valente 2011). When the customer base is larger, relying on self-identification can be a costly and complicated procedure that may not provide the full picture of customer connectivity. Partly for this reason, many of firms' recent efforts to assess customer connectivity and its implications are based on the use of online data. Yet obtaining large-scale (online) customer connectivity data for a specific product can necessitate considerable spending on an online presence and can be problematic in terms of privacy. Furthermore, there are indications that many of the connections in online social networking sites, a major source of customer connectivity data, are not good representations of actual influence (e.g., Trusov, Bodapati, and Bucklin 2010). Therefore, care should be taken to ensure that consumption-related opinion leaders are indeed identified.

Similarly, firms should ensure that they can actually identify customers who are expected to be revenue leaders. Predicting CLV may be nontrivial given fluctuations in consumption (Malthouse and Blattberg 2005), and yet given rich enough data, recent research has suggested that advanced CLV modeling can effectively predict the profitability of customers (Rust, Kumar, and Venkatesan 2011). In the case of new product seeding, such predictions can be particularly challenging due to possible lack of information on previous purchases. The application of CLV models is most straightforward in settings in which the firm's relationship with the customer is ongoing, enabling the firm to collect data on consumption patterns for the specific product. However, note that CLV prediction also plays a major role in firms' efforts to acquire customers and to develop relationships (Blattberg, Kim, and Neslin 2008; Kumar et al. 2008). To predict CLV in such cases, firms use a variety of information sources that include household characteristics, analogies from the consumption of similar products, reactions to promotions, and environmental factors.

We should also note that in many cases, even though the specific product is new to the customer, the firm may still have a relationship with the customer pertaining to multiple other products. The consumer's previous patterns of consumption may provide the firm with information to help predict the profitability from the new product introduced. This is especially true in situations in which a new product is actually a new generation of a previously consumed product. For example, pharmaceutical companies that have information on the prescription volume of a current drug can use it to estimate the lifetime value of a physician for a new drug (Iyengar, Van den Bulte, and Valente 2011). That said, for a radically new product associated with high uncertainty regarding acceptance and usage, an effort to target revenue leaders may be less straightforward.

Overall, note that for opinion leaders and revenue leaders, seeding does not demand predicting the exact individual-level value, because it is sufficient to predict that the consumer belongs to the upper group. In both cases, as in other marketing phenomena, prediction can sometimes be far from perfect. The question remains which of the two is more difficult to predict. Although there is no empirical work on such comparison, it seems that firms should have more experience predicting customers' CLV than their social influence.

The Cost of Seeding

The cost of seeding is a function of the cost of identifying opinion leaders and revenue leaders (discussed previously) in addition to the cost of convincing the seed to adopt the product early on. The latter cost may be influenced by multiple factors. In the case of revenue leaders, one could argue, for example, that they risk more by adopting early and may therefore need more persuasion. Conversely, revenue leaders may be brand-loyal customers who enjoy the opportunity to adopt early. In the case of opinion leaders, if firms frequently approach them (as occurs in the case of influential bloggers), it may be more difficult to convince them to adopt a product. Alternatively, firms can create a de facto opinion leader campaign using incentivized word-of-mouth agent programs (Godes and Mayzlin 2009), which may not be that costly. More research is needed to make generalizations with regard to the cost of seeding.

Our results provide some intuition regarding how much it is worth to invest in opinion leader and revenue leader seeding. In Web Appendix VIII (www.marketingpower.com/jm_webappendix), we illustrate a seeding approach that takes our results into account. The basic idea is that the cost of seeding a customer can be expressed as a certain fraction of his or her lifetime value. Although the cost of seeding each group may vary by market, given a specific market, marketers can evaluate whether it is worthwhile to invest in one targeting option, given the cost of the alternative. For example, if marketers know the cost of seeding an opinion leader (expressed as percent CLV), they can determine the cost per revenue leader that would make revenue leader seeding more profitable.

Using the average total value contribution we determined for different seed sizes, we can do this calculation, which appears in Table WA8A in Web Appendix VIII (www.marketingpower.com/jm_webappendix). The results are consistent with the general theme of the findings: For low percent seeding, it is worthwhile to invest in opinion leaders even if the cost to obtain them is relatively high. Yet in general, as seeding percentages go up, it becomes worthwhile to invest in revenue leaders, even when the cost of targeting them is higher than the cost of targeting opinion leaders.

Limitations and Further Research

We have mentioned some limitations and future directions in the preceding section, and yet further elaboration is warranted. Our study is a first exploration of the full implications of revenue leader targeting, so we aimed to keep the agent-based approach relatively parsimonious so we could focus on the basic dynamics. However, these dynamics can and should be further explored. Specifically, we suggest seven promising areas of further research. First, an in-depth examination of the role of heterogeneity in the diffusion parameters and in additional network structures is a worthwhile avenue. Second, the role of competition is of much interest as well. We focused our analysis on acceleration-driven value, and yet the consequences of acquiring customers who otherwise might have gone to a competing firm (Libai, Muller, and Peres 2013) may amplify the assortativity effect.

A third notable issue is that of negative word of mouth. It is reasonable to expect that in the same way that assortativity drives higher value for revenue leaders, it can also cause greater damage following a brand crisis or perpetuate more negative word of mouth within this population. As researchers gain access to data that include both network connectivity and consumption, they can further study the heterogeneity in assortativity across markets and its antecedents. A fourth question pertains to the applicability of our results to targeting for mature products. For mature products, the friends of the seeded person may already have been affected over time, especially given the CLV assortativity discussed here. Thus, the revenue leader's potential to influence unaffected consumers may be small. It has been suggested, for example, that loyal customers may be less likely to contribute as word-of-mouth agents for a restaurant chain (Godes and Mayzlin 2009). Examining the targeting of revenue leaders and opinion leaders in the context of more mature products is thus a fruitful research direction.

A fifth worthwhile avenue of exploration involves the possibility of using a hybrid strategy for seeding. When considering the options firms face, researchers largely focus on the benefits of targeting a "pure" population (e.g., either revenue leaders or opinion leaders). This is because the range of possibilities in combining pure targeting strategies into a hybrid targeting approach is extremely large, and benefits of different approaches may be highly dependent on the specific setting. We conducted an analysis (presented in Part 1 of Web Appendix IX at www.marketingpower.com/jm_webappendix), in which we investigated the effect of a hybrid strategy in which half the targeted population are opinion leaders and half are revenue leaders. Comparing the results with the ones obtained in Table 2, we observe that the general pattern of value created is consistent with what we observed previously, and the resultant total value is roughly the same or lower than the best "pure" strategy used. However, there may be other hybrid strategies that can be taken, and this presents a worthwhile question for future investigation.

The sixth issue to explore involves the possibility of error in the identification of either revenue leaders or opinion leaders. Our analysis explores the consequences of correct targeting of both, and yet, as discussed previously, often this is not the case. For a simple case in which only 50% of revenue leaders and 50% of opinion leaders are correctly identified, we observe (see Table WA9B in Part 2 of Web Appendix IX at www.marketingpower.com/jm_webappendix) that indeed, the total value goes down, and yet the general pattern of social and direct value stays the same in both cases. This will change if there is evidence that a firm can predict one of them better than the other, a phenomenon for which there is little or no comparative research to date and that may also be market specific, a topic of much interest for further research.

Finally, future work should further explore the nature and dynamics of CLV assortativity; specifically, a topic that warrants further investigation is the driver of assortativity. In a general sense, CLV assortativity can stem from two main sources (see, e.g., Schmitt, Skiera, and Van den Bulte 2011): selectivity in tie formation and contagion. The former involves people's tendency to seek out and interact with people who are like them. The latter reflects the finding that over time, people influence their network neighbors to behave similarly to themselves. Most of the literature on homophily and network assortativity focuses on selectivity rather than on contagion partly because related variables such as age, gender, and race cannot be changed. Our framework here does not explicitly make an assumption on this issue, and yet the CLV assortativity we model may be seen as closer to selectivity because we assume that it is exogenous and does not change following the adoption process. Theoretically, we could argue that the modeling approach we present is indifferent to the source of CLV assortativity, because even given contagion, if the contagion in CLV immediately follows the contagion in adoption, the results will remain the same. The question is this: What happens if CLV contagion is slower than the adoption contagion? Given the lack of empirical findings on this subject, we leave this exploration to further research.

Conclusion

Two of the major developments of the marketing discipline in the past two decades are the realization of the importance of the value of the customer to making informed marketing decisions and the recognition that customer connectivity necessitates a "network view" of customer decision making and profitability. This study combines the two concepts by investigating the nontrivial value created by revenue leaders and opinion leaders. We are confident that as more data that combine social networks and consumption become available, researchers' and marketers' ability to make informed decisions in this intriguing area will be substantially enhanced.

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